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Categorization of Animal Sounds Using Algorithms from Diverse Applications

G. A. Clark

October 22, 2009

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October 26, 2009 through October 30, 2009

Lawrence Livermore National Laboratory

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Categorization of Animal Sounds Using Algorithms From Diverse Applications

October 26, 2009

Grace A. Clark, Ph.D., IEEE Fellow

Eng/NSED/Systems and Intelligence Analysis Section

Lawrence Livermore National Laboratory, P. O. Box 808, Livermore, CA 94551

LLNL-XXX-XXXX

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Auspices and Disclaimer

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Disclaimer

Agenda

- Introduction, Motivation
- Animal Acoustics Data and Processing Approaches
- Example Signal and Image Processing Algorithms
- Example Application: ***Automatic Event Picking for Seismic Oil Exploration***
- Summary and Discussion

Motivation: *Diverse Problems, Similar Solutions*

- **Use the Philosophy/Theme:** ***Diverse Problems, Similar Solutions***

  - An Interdisciplinary team approach

- **My technical specialty is *statistical signal/image processing, estimation/detection, pattern recognition, sensor fusion and control***

- **My application areas are in acoustics, electro-magnetics and particle physics, including:**
  - **Seismic oil exploration and seismic treaty verification**
  - **Acoustic classification/detection of artificial heart valve damage**
  - **Ultrasonic nondestructive evaluation of materials**
  - **Acoustic classification/detection of facility activity**
  - **Buried land mine detection (IR, Visible Wavelength, GPR, UV)**

- **The session organizers invited me to the ASA session on Animal Acoustics in Portland May 2009 – look at it from a signal processing point of view**

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Examples of Dolphin Acoustic Data

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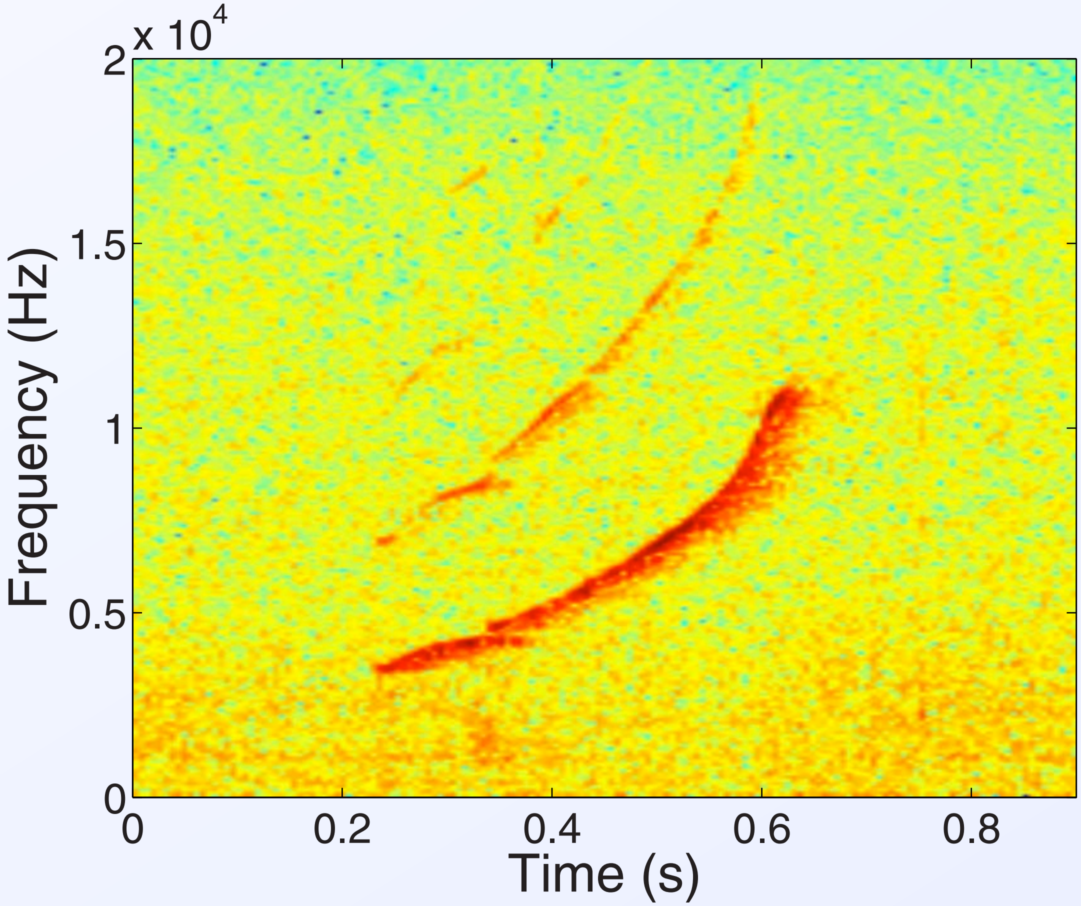
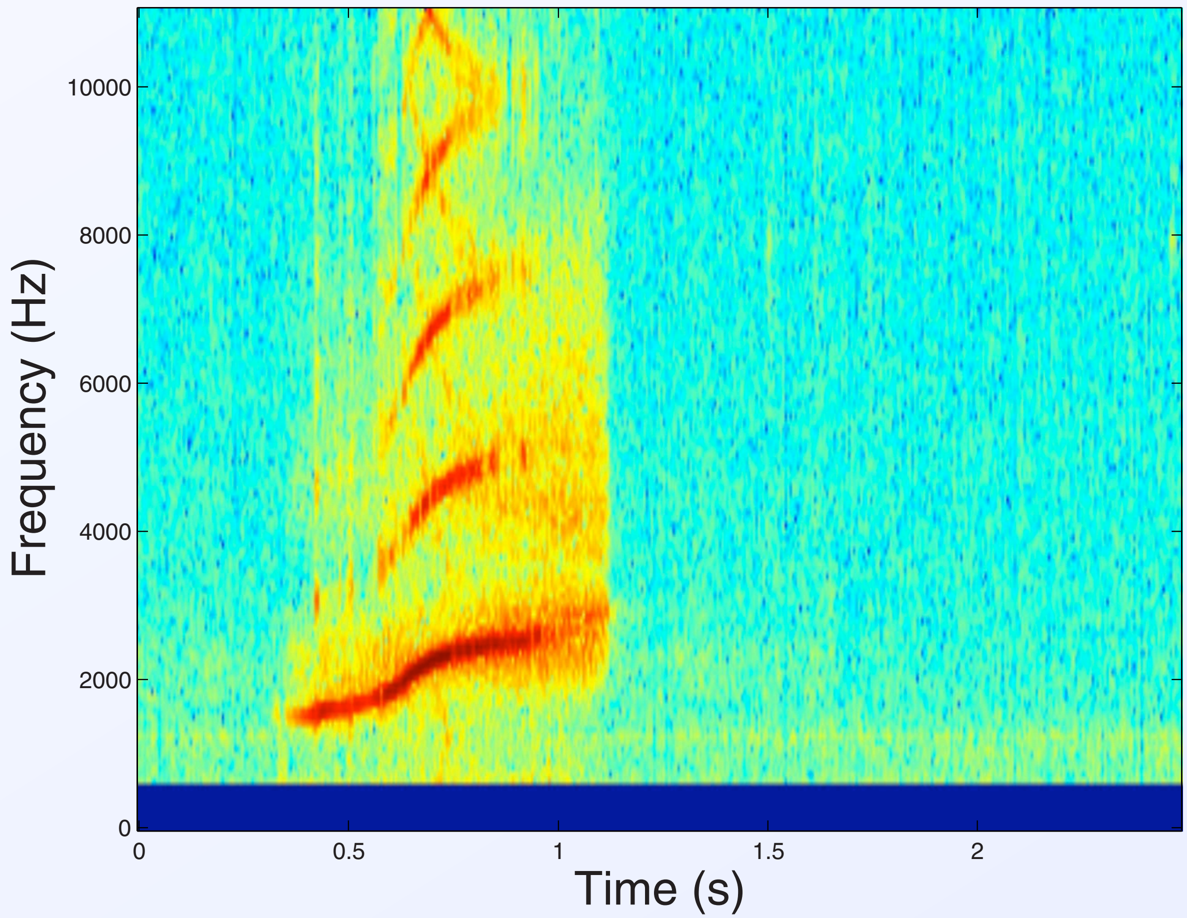
Dolphin Whistle *Spectrograms Show a Narrowband Frequency-Modulated Contour that is Smooth and Frequency-Localized**



Note the Harmonics

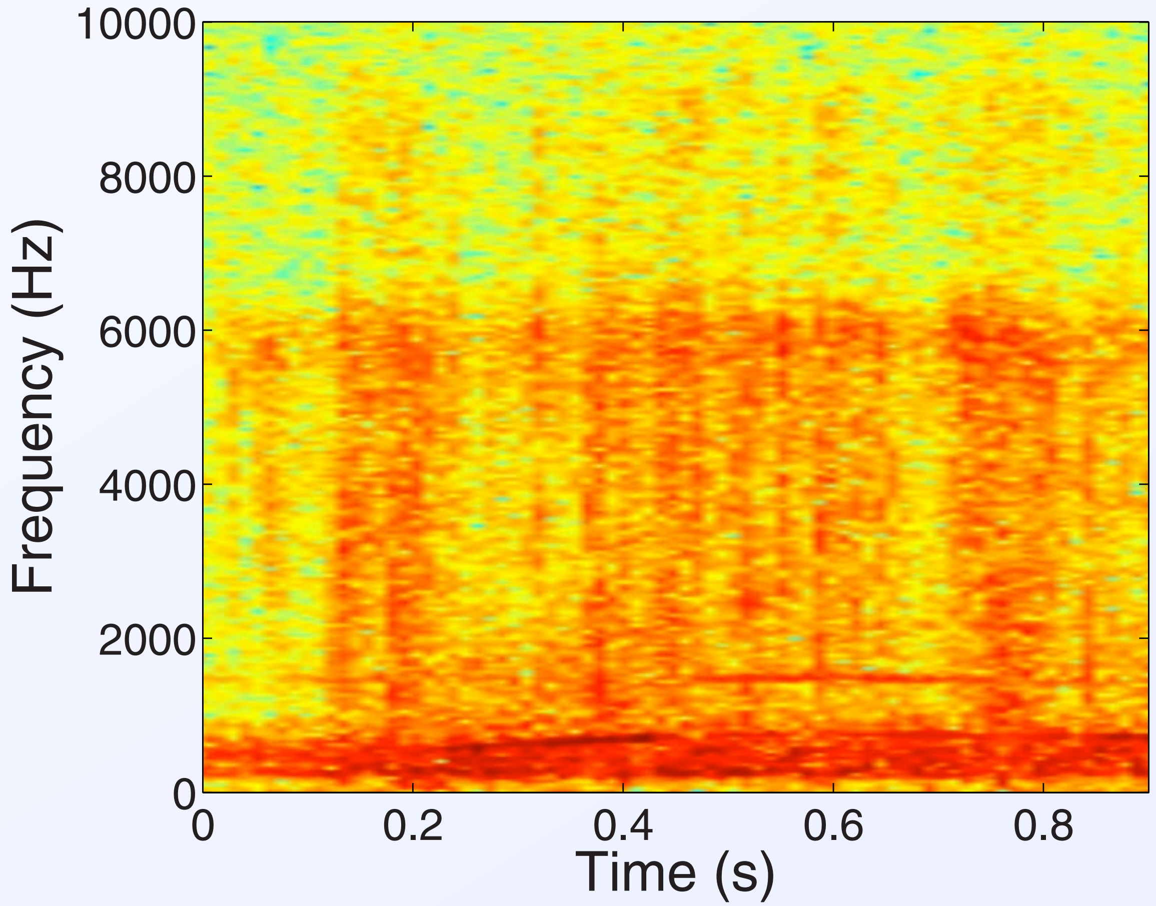
* Mallawaarachchi, S. H. Ong, M. Chitre, E. Taylor, *"Spectrogram denoising and automated extraction of the fundamental frequency variation of dolphin whistles,"* JASA 124 (2), August, 2008, pp.1159-1170.

Dolphin Whistle *Spectrograms Can Contain Strong Harmonics**



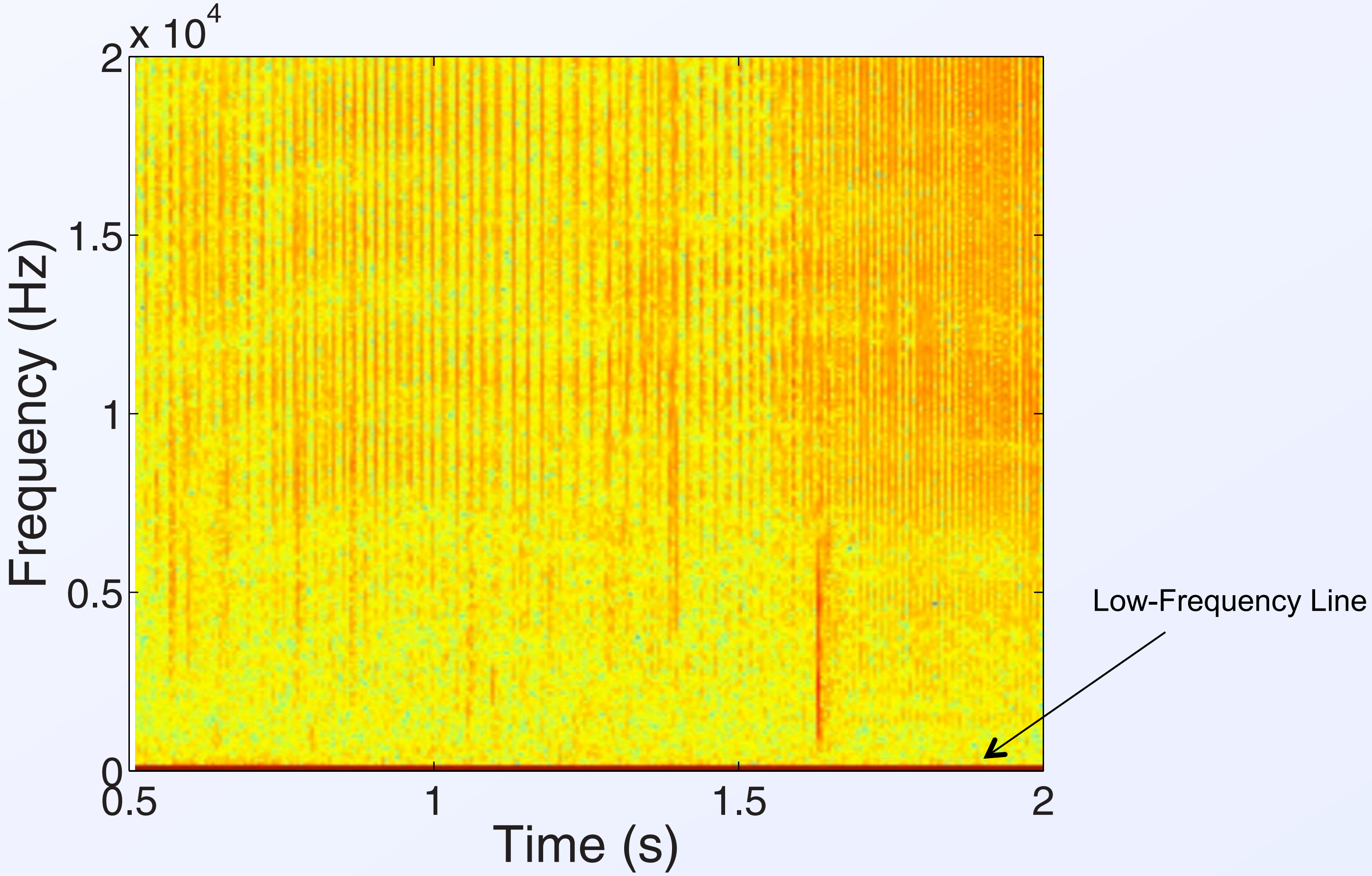
* Mallawaarachchi, S. H. Ong, M. Chitre, E. Taylor, *"Spectrogram denoising and automated extraction of the fundamental frequency variation of dolphin whistles,"* JASA 124 (2), August, 2008, pp.1159-1170.

Dolphin Echolocation Clicks *are Short-Duration Broadband Signals Showing Vertical Line Patterns in the Spectrogram**



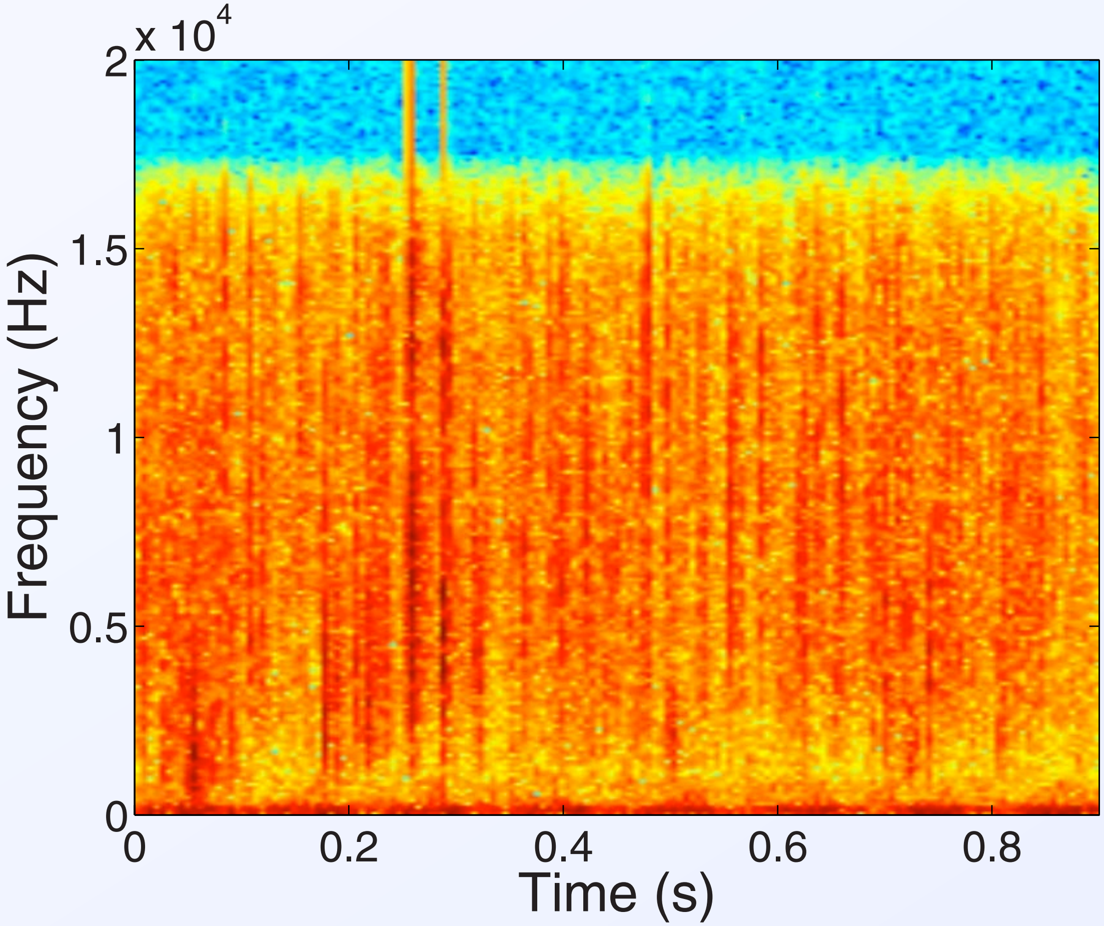
* Mallawaarachchi, S. H. Ong, M. Chitre, E. Taylor, *"Spectrogram denoising and automated extraction of the fundamental frequency variation of dolphin whistles,"* JASA 124 (2), August, 2008, pp.1159-1170.

Signals Generated by Mechanical Processes *Generally Have Low Constant Frequencies => Horizontal Lines at Low Frequency*



* Mallawaarachchi, S. H. Ong, M. Chitre, E. Taylor, *"Spectrogram denoising and automated extraction of the fundamental frequency variation of dolphin whistles,"* JASA 124 (2), August, 2008, pp.1159-1170.

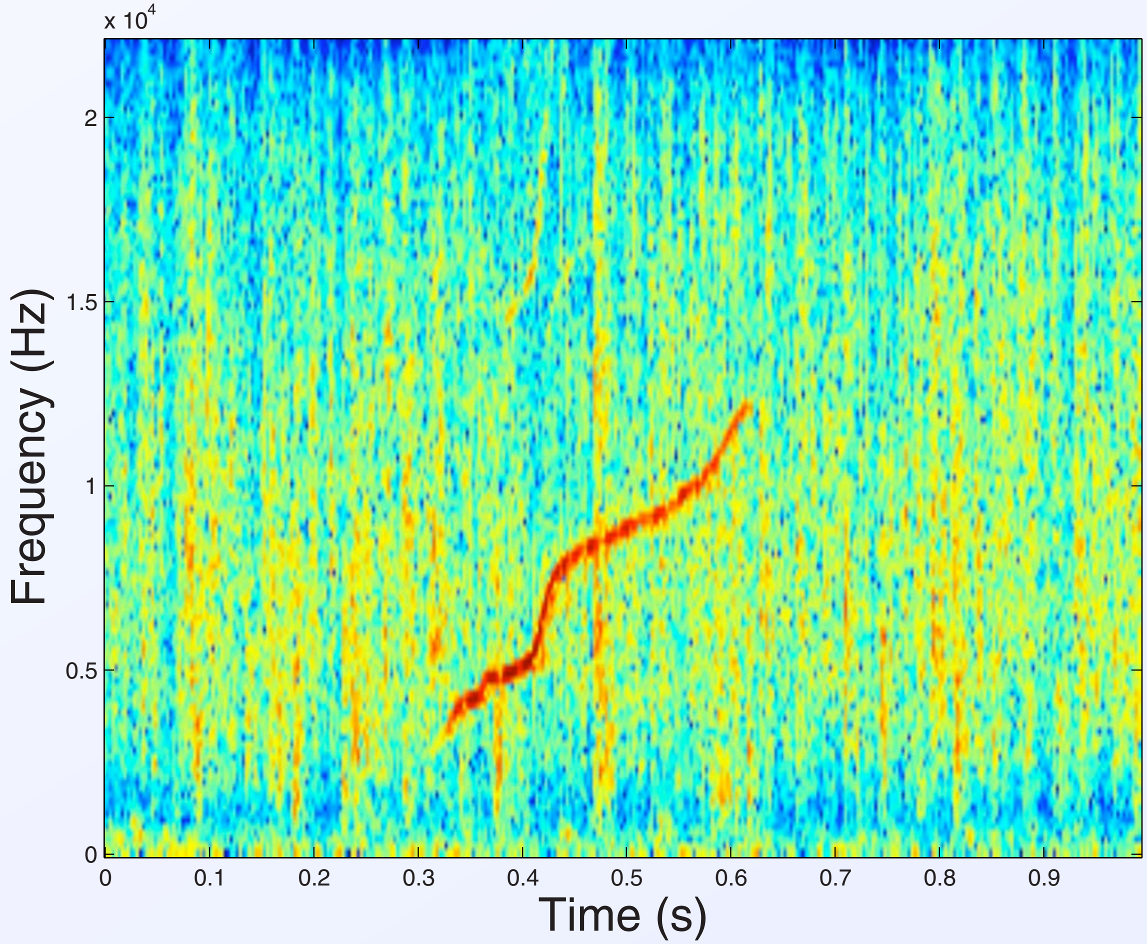
Ambient Noise in Warm Shallow Water Worldwide *is Dominated by Broadband Crackling or Popping from Snapping Shrimp**



- *One shrimp snapping sound makes a narrow vertical line*
- *Many shrimp sounds overlap and are not as clear as dolphin clicks*

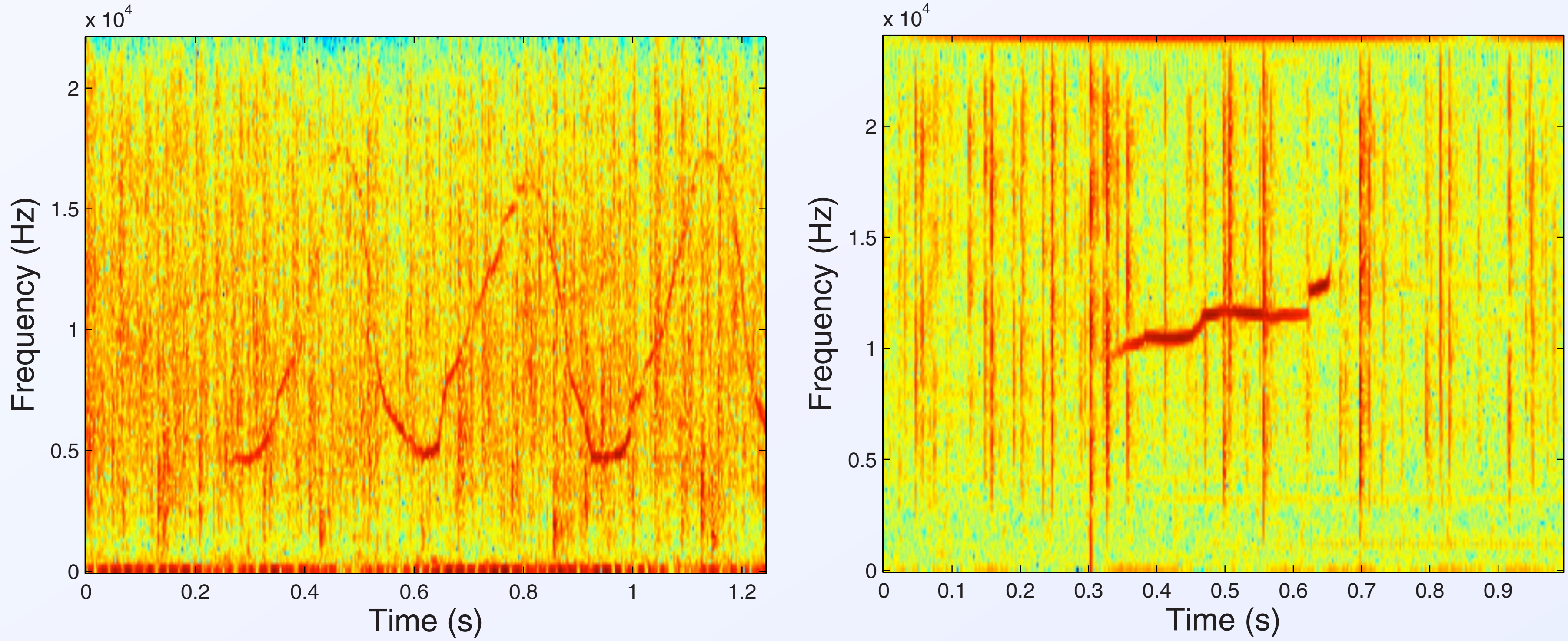
* Mallawaarachchi, S. H. Ong, M. Chitre, E. Taylor, *"Spectrogram denoising and automated extraction of the fundamental frequency variation of dolphin whistles,"* JASA 124 (2), August, 2008, pp.1159-1170.

A Dolphin Whistle Corrupted by Snapping Shrimp Noise*



* Mallawaarachchi, S. H. Ong, M. Chitre, E. Taylor, *"Spectrogram denoising and automated extraction of the fundamental frequency variation of dolphin whistles,"* JASA 124 (2), August, 2008, pp.1159-1170.

Two Problematic Dolphin Whistle Spectrograms



* Mallawaarachchi, S. H. Ong, M. Chitre, E. Taylor, *"Spectrogram denoising and automated extraction of the fundamental frequency variation of dolphin whistles,"* JASA 124 (2), August, 2008, pp.1159-1170.

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Signal and Image Processing Algorithms

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Generally, Methods for Classification, Inverse Problems and Fusion are Either “Data-Based” or “Model-Based”

Data-Based Methods

Little prior knowledge available (e.g. Physics Models, priors).

Develop nonparametric or “Black Box” models from measured data only.

Examples:

-Clustering

-K-Nearest Neighbor

-Feature Analysis

-CART (Classification and Regression Trees)

-Neural Networks

-Bayesian Classifier(s)

Model-Based Methods

Maximum Likelihood/ Optimal Least Squares

Use least squares optimization algorithms to minimize mean-square error between model predictions and observed measurements.

Examples:

-Wiener/Kalman Filters (Linear)

-Extended Kalman Filters (Linearized Nonlinear)

Bayesian Methods

Use probabilistic sampling algorithms to estimate likelihoods and posterior probabilities comparing model predictions and observed measurements.

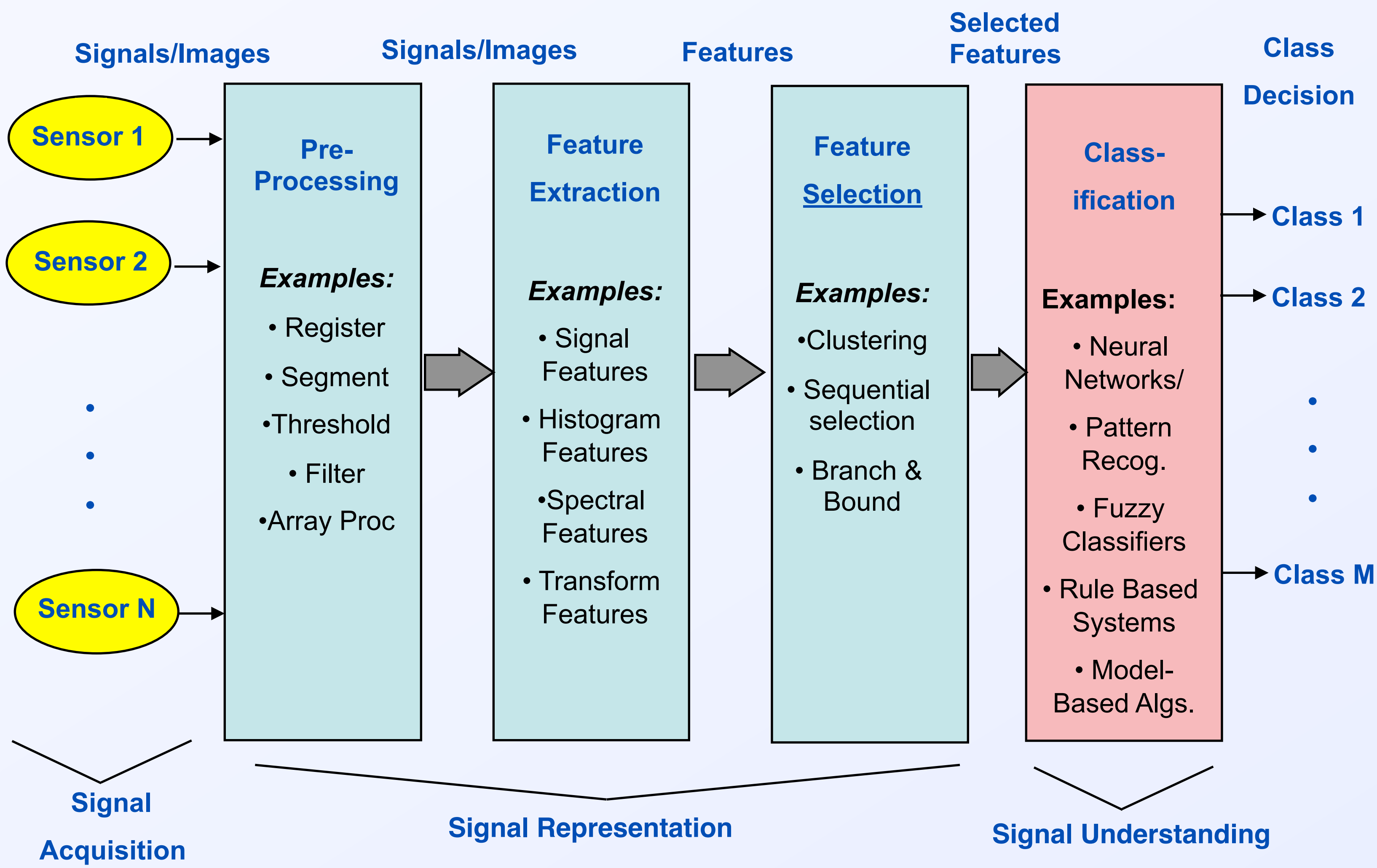
Examples:

-Markov Chain Monte Carlo

-Sequential Monte Carlo

-Bayesian Belief Nets

Target Recognition Depends Heavily on the Judicious Choice of Signal / Image Features

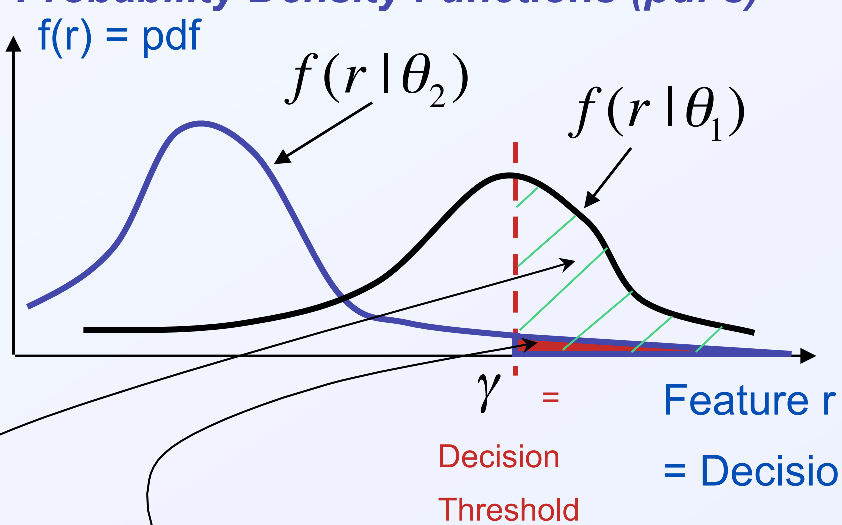


Hypothesis Testing Generates a Receiver Operating Characteristic (ROC) Curve

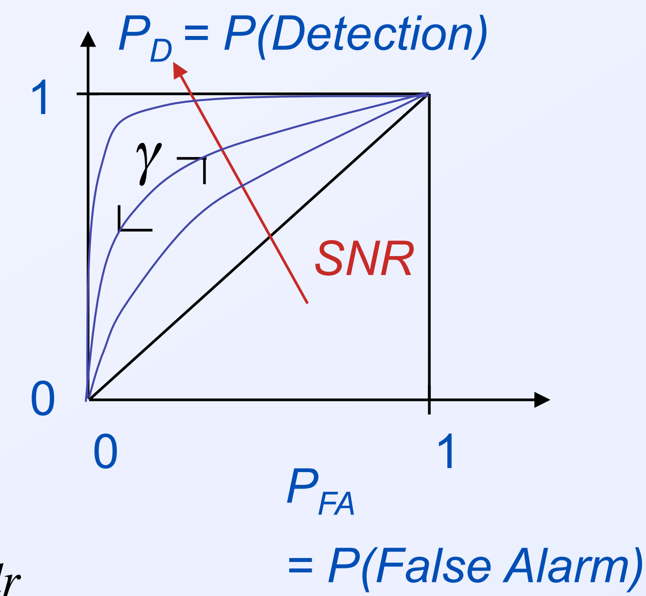
t = Time
s(t) = Signal of Interest
v(t) = Noise or "Background"
r(t) = s(t) + v(t) = Measurement
γ = Decision Threshold

$$\text{Hypothesis } \theta_1 \text{ (Active)}: \quad r(t) = s(t) + n(t)$$
$$\text{Hypothesis } \theta_2 \text{ (Inactive)}: \quad r(t) = n(t)$$

Probability Density Functions (pdf's)



ROC Curve



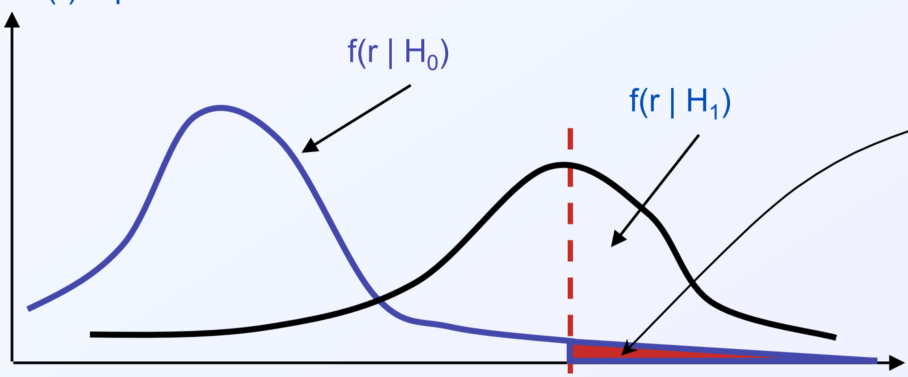
$$P(\text{False Alarm}) = P_{FA}(\gamma) = \int_{\gamma}^{\infty} f(r \mid \theta_2)\, dr$$

$$P(\text{Detection}) = P_D(\gamma) = \int_{\gamma}^{\infty} f(r \mid \theta_1)\, dr$$

The ROC Is Computed by Integrating Under the Conditional Probability Density Functions for a Given Threshold r_0

r = Detection Statistic (Grey Scale Values)

For Example: Posterior Probabilities $P(H_1 \mid X)$ or $P(H_0 \mid X)$



$$P(H_1 \mid H_0) = P_{FA}(r_0) = \int_{r_0}^{\infty} f(r \mid H_0)\, dr = 1 - P_{SPEC}(r_0)$$

$$P(H_1 \mid H_1) = P_D(r_0) = \int_{r_0}^{\infty} f(r \mid H_1)\, dr = 1 - P(H_0 \mid H_1) = 1 - P_{MISS}(r_0)$$

$$P(H_0 \mid H_1) = P_{MISS}(r_0) = \int_{-\infty}^{r_0} f(r \mid H_1)\, dr = 1 - P(H_1 \mid H_1) = 1 - P_D(r_0)$$

$$P(H_0 \mid H_0) = P_{SPEC}(r_0) = \int_{-\infty}^{r_0} f(r \mid H_0)\, dr$$

The Confusion Matrix (Contingency Table) Can Be Obtained from a Finite Number of Samples

Truth / Decision	θ_1	θ_2
θ_1	$P(\theta_1 / \theta_1) = P(Detection)$ $= \dfrac{No.\ Samples\ Classified\ \theta_1}{No.\ \theta_1\ Samples}$	$P(\theta_1 / \theta_2) = P(\boldsymbol{False\ Alarm})$ $= \dfrac{No.\ Samples\ Classified\ \theta_1}{No.\ \theta_2\ Samples}$
θ_2	$P(\theta_2 / \theta_1) = P(\boldsymbol{Miss})$ $= \dfrac{No.\ Samples\ Classified\ \theta_2}{No.\ \theta_1\ Samples}$	$P(\theta_2 / \theta_2) = Specificity$ $= \dfrac{No.\ Samples\ Classified\ \theta_2}{No.\ \theta_2\ Samples}$

$$P(\theta_1 | \theta_1) + P(\theta_2 | \theta_1) = 1$$

$$P(\theta_1 | \theta_2) + P(\theta_2 | \theta_2) = 1$$

$$P(Correct\ Classification) = P(CC) = P(\theta_1 | \theta_1)P(\theta_1) + P(\theta_2 | \theta_2)P(\theta_2)$$

Feature Analysis Is Key to Event Flaw Recognition

Feature Extraction

- Raw data z(t), I(x,y)
- |z(t)|, |I(x,y)|
- Histogram features
- Spectral features
  - Ratios of peaks
  - Power spectral density
  - Spectrograms
  - Scalograms (wavelets, hierarchical transforms)
  - Higher-order spectra
- Other features (shape, size)

Feature Selection

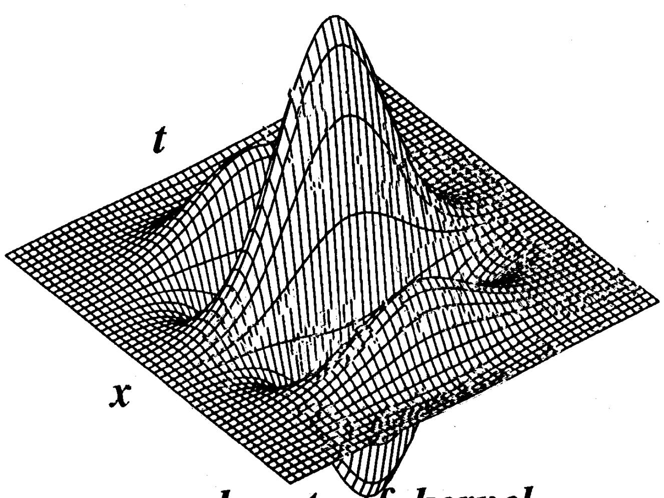
- Use displays to obtain physical intuition
  - Feature space plots
  - SNR vs. freq.
  - etc.
- Feature selection algorithms to rank order features according to class separability measures.
- Relate feature space to physics

Gabor transform features extract information on the structural properties of image

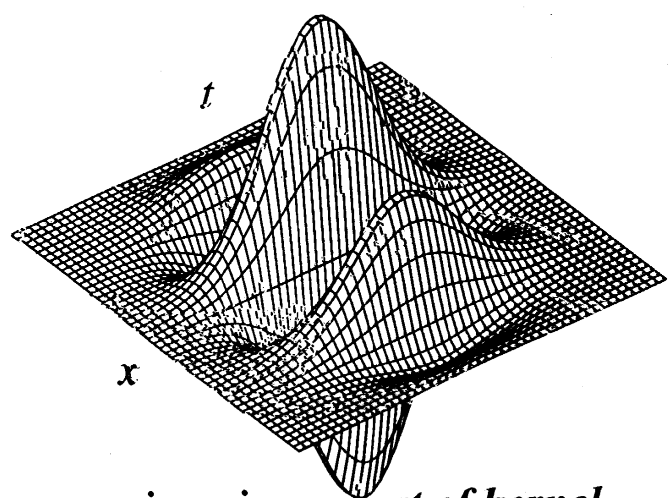
- **2D Gabor filter kernels**

$$h(x,t) = g(x',t')\, e^{i2\pi(kx+wt)}$$

$$g(x,t) = e^{-\frac{1}{2}\left[\left(\frac{x}{\sigma_x}\right)^2 + \left(\frac{t}{\sigma_t}\right)^2\right]} \qquad \begin{bmatrix} x' \\ t' \end{bmatrix} = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} x \\ t \end{bmatrix} \qquad \theta = \mathrm{atan}\left(\frac{k}{w}\right)$$



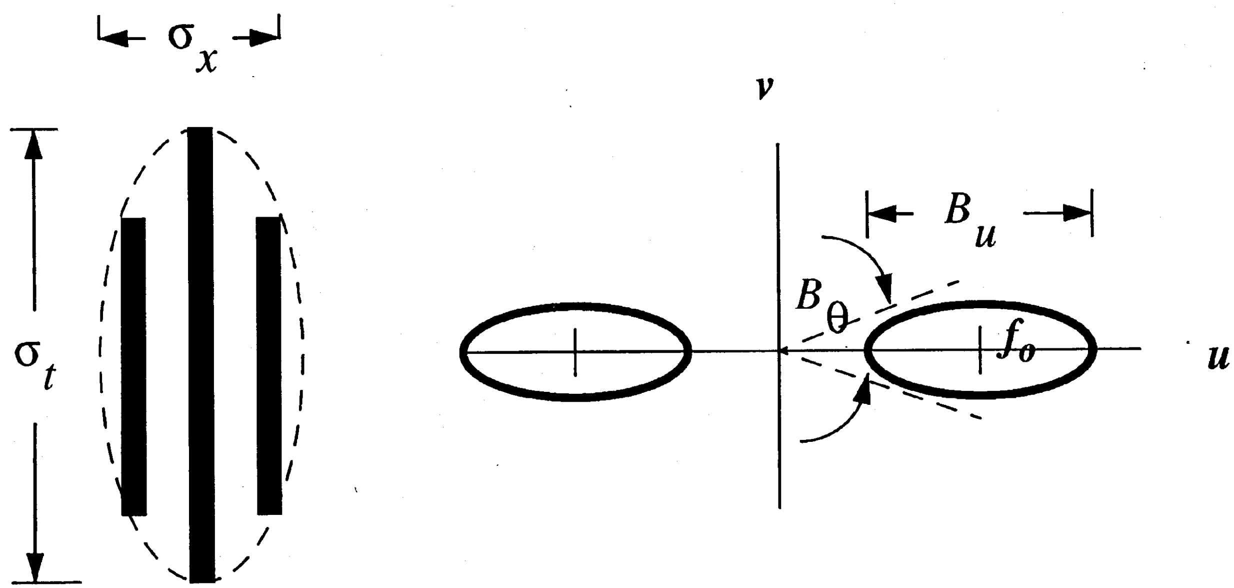
real part of kernel



imaginary part of kernel

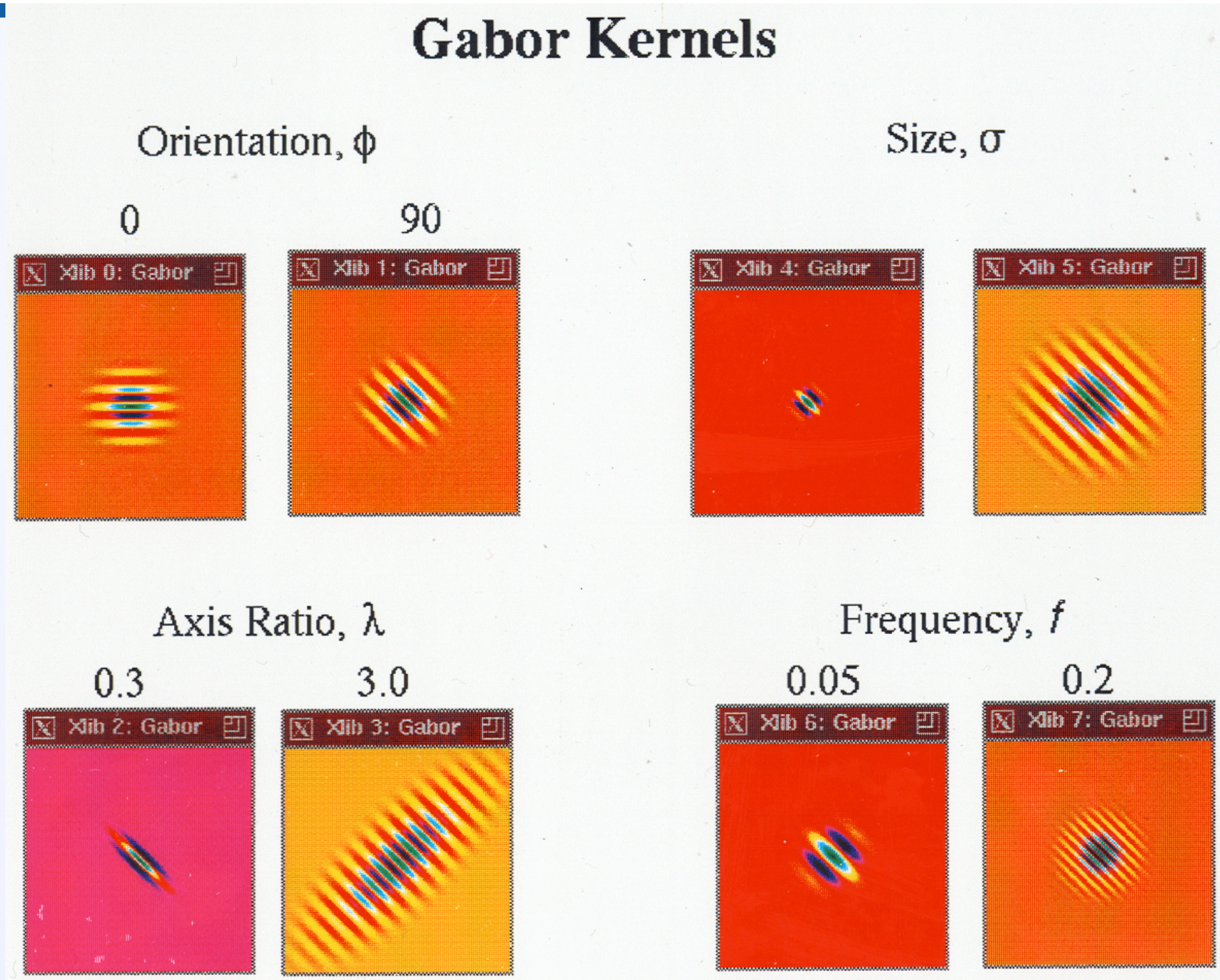
Gabor frequency response : tunable on orientation bandwidth and frequency bandwidth

$$H(u, v) = e^{-2\pi^2\left[(u-k)'^2\sigma_x^2 + (v-w)'^2\sigma_t^2\right]} \qquad f_o = \sqrt{k^2 + w^2}$$

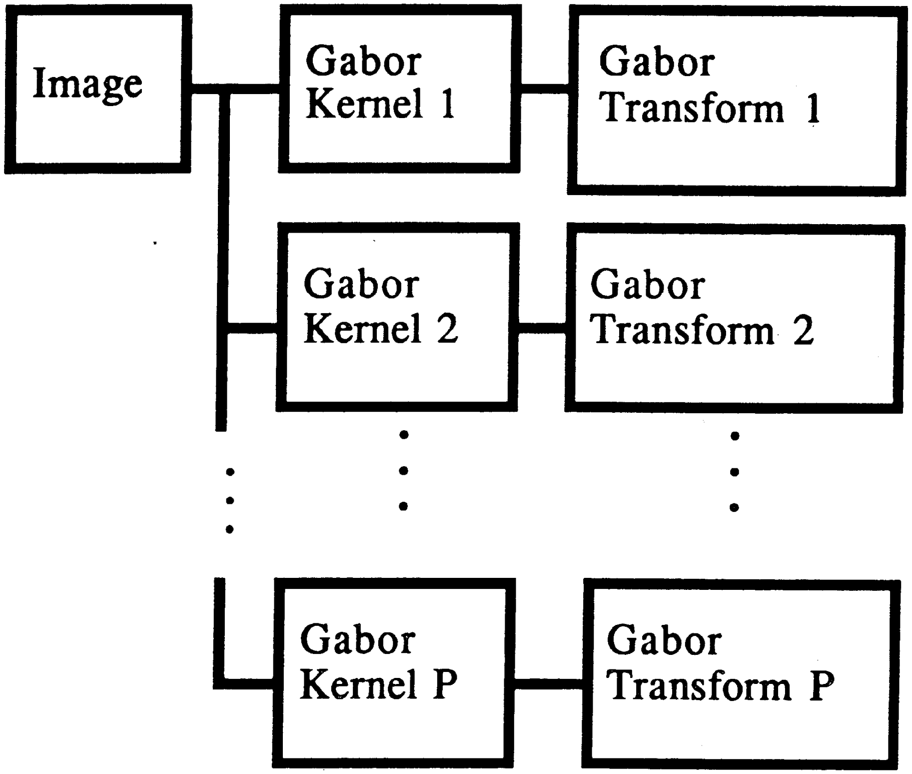


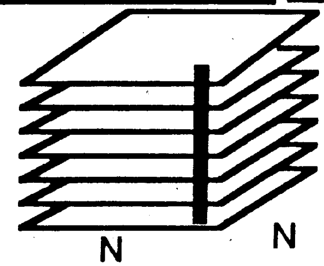
orientation bandwidth $B_\theta = 2\tan^{-1}\left(\frac{0.1874}{f_o\sigma_t}\right)$

frequency bandwidth $B_u = \log_2\left(\frac{f_o\sigma_x + 0.1874}{f_o\sigma_x - 0.1874}\right)$

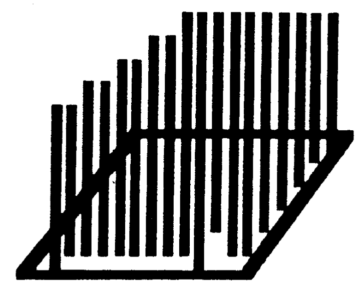

Gabor Kernels
Orientation, ϕ
0
90
Xlib 0: Gabor
Xlib 1: Gabor
Size, σ
Xlib 4: Gabor
Xlib 5: Gabor
Axis Ratio, λ
0.3
3.0
Xlib 2: Gabor
Xlib 3: Gabor
Frequency, *f*
0.05
0.2
Xlib 6: Gabor
Xlib 7: Gabor

We Create a Gabor Data Block, then Reduce its Dimensionality

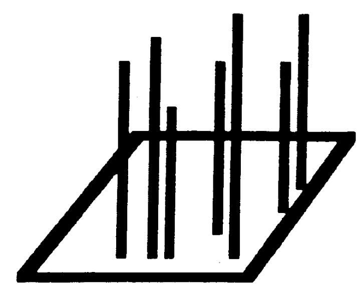




Gabor Data Block



Feature Vectors (FV's)



Most Important FV's

Feature Selection Example: *Automatic Event Picking for Seismic Oil Exploration*

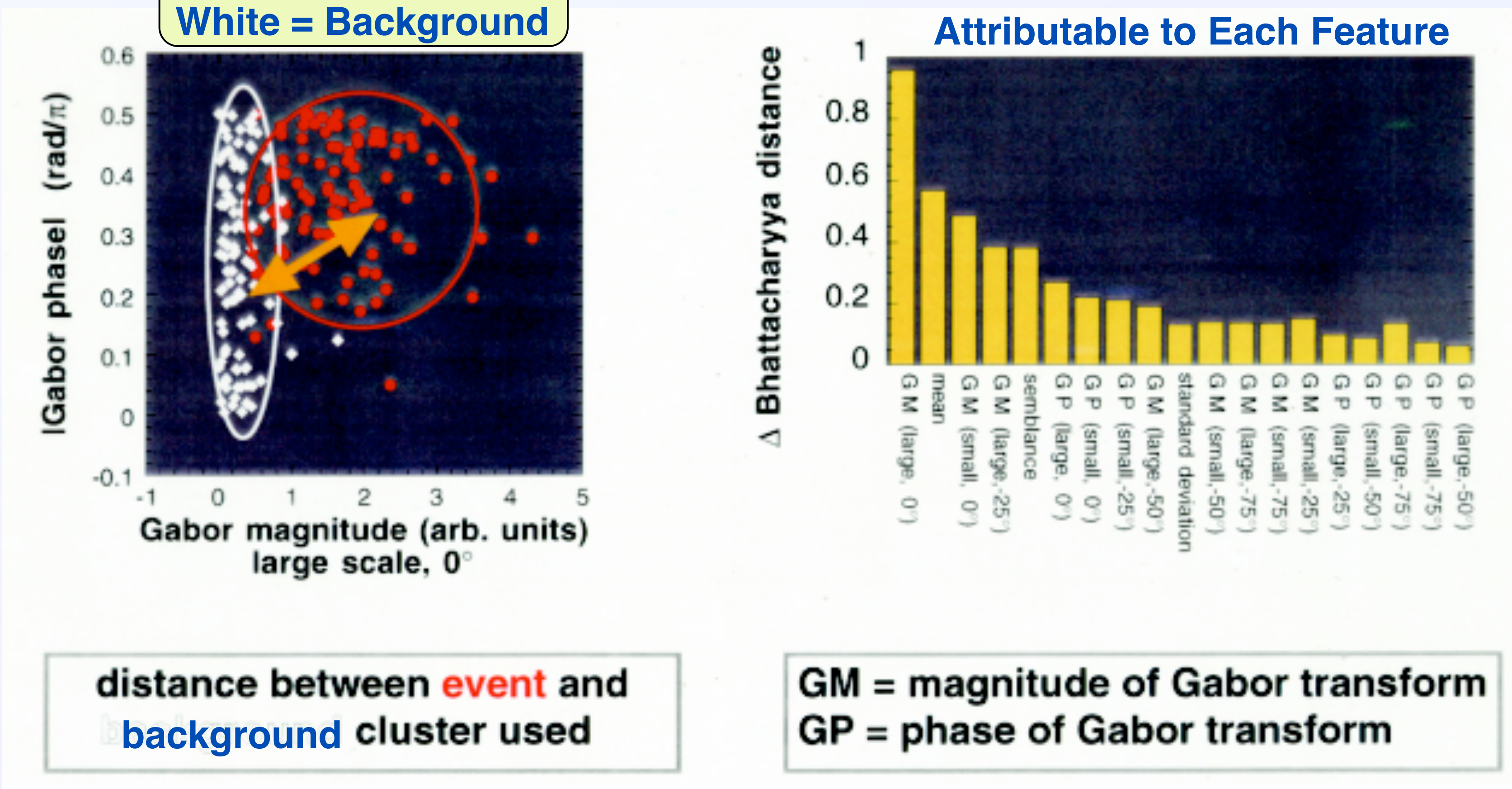
Rank Order the Features According to the Change In the Bhattacharyya Distance, Using Sequential Feature Selection

Red = Events

White = Background

Increase in the Bhattacharyya Distance

Attributable to Each Feature



Typical Approaches Involve Pre-processing, Pixel Classification, Region Formation and Post-processing

Raw Images → **Pre-Processing To Improve SNR, Remove Distortion** → **Pixel Classification and Labeling To Classify Pixels as Event or Background** → **Event Region Formation to Group Pixels into Candidate Event Regions** → **Post-Processing to Improve SNR** → Event Locations

Example Pre-Processing Algorithms:

- Filtering
- CFAR (Constant False Alarm Rate) Detection
- Deconvolution, Superresolution

Example Pixel Classification Algorithms:

- Feature extraction
- Feature selection
- Probabilistic Neural Network Classification

Example Region Formation Algorithms:

Region growing/ merging/ Connected Components Analysis

Example Post-Processing Algorithms:

- Morphological Filtering
- Size and Shape Constraints
- Performance Estimation: P(Correct Classification)

Pixel Classification and Labeling

Are Likely to Involve Supervised Learning

Image → **Feature Extraction To Quantify Events and Background** → **Feature Selection to Find the Best Subset of the Features Extracted** → **Pixel Classification to Classify Pixels as *Event* or *Background*** → **Image Labeling to Form a Classified / Labeled Image** → Labeled Image

Example Feature Types:

- Histogram / Amplitude
- Texture
- Multi-Resolution (DOG, Wavelets, etc.)
- Etc.

Example Feature Selection Algorithms:

- Sequential Forward Selection
- Branch and Bound

Example Classification Algorithms:

- Probabilistic Neural Network (PNN)
- Statistical and/or Neural Network Classifiers

Candidate Labeling Algorithms:

- Binary image: 1 = event pixel, 0 = background pixel
- Posterior Probability P(EventIX) at Each Pixel

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Example Application:

Automatic Event Picking for Velocity Estimation in Seismic Oil Exploration

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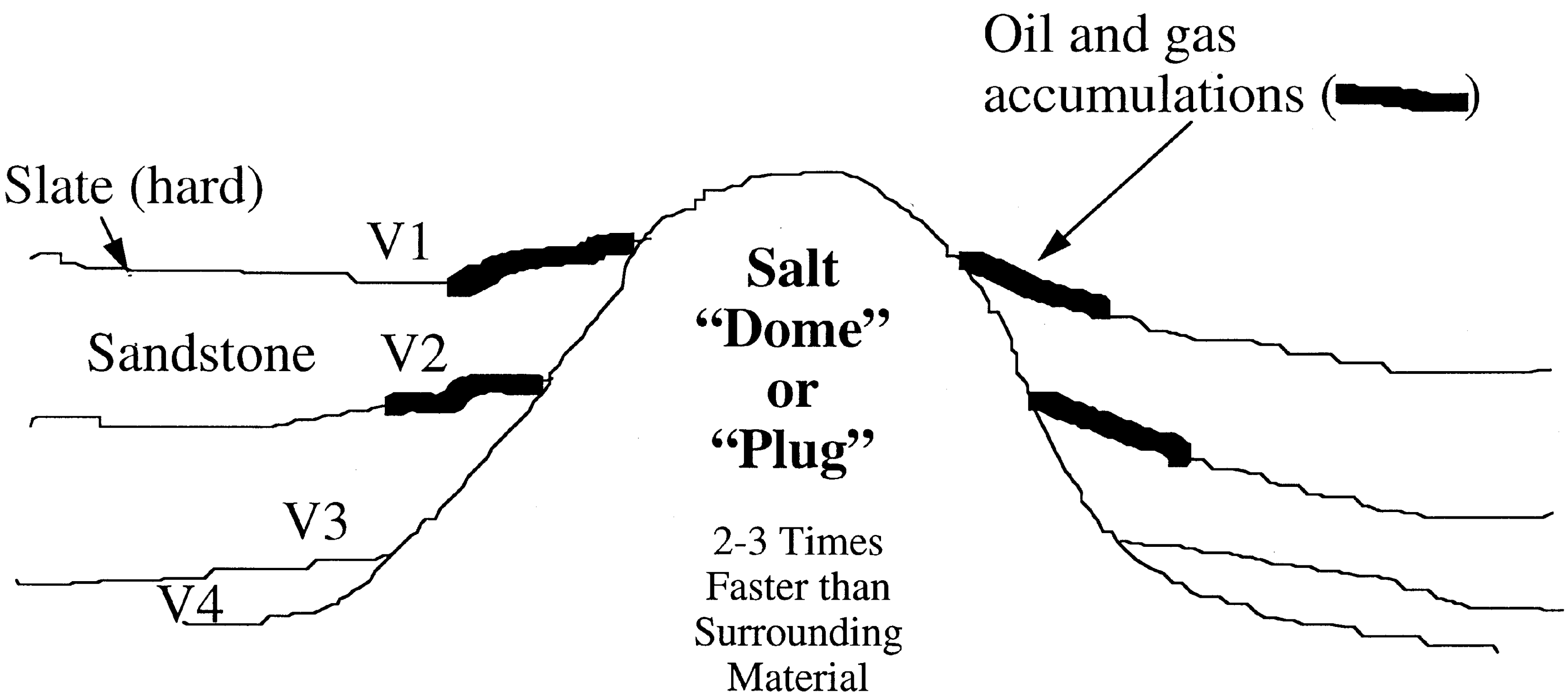
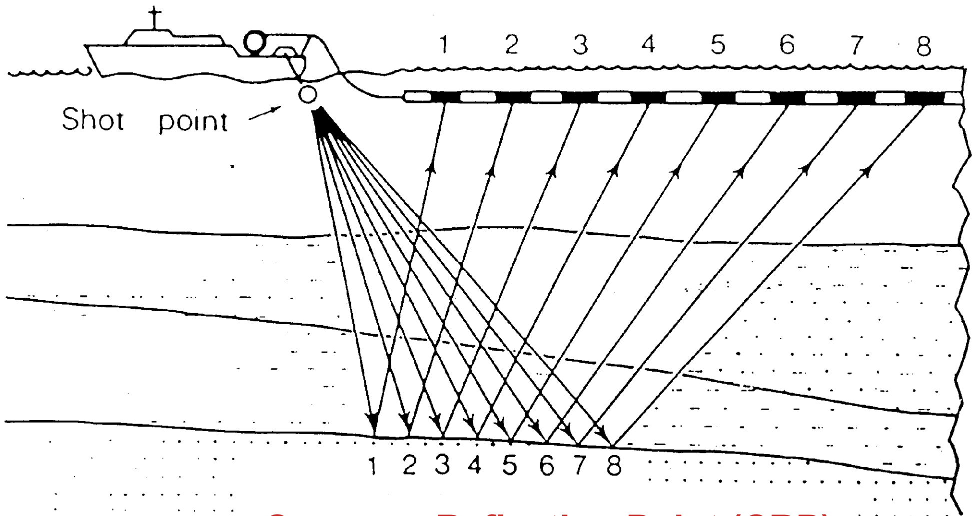
Oil Companies Search for Geological Structures

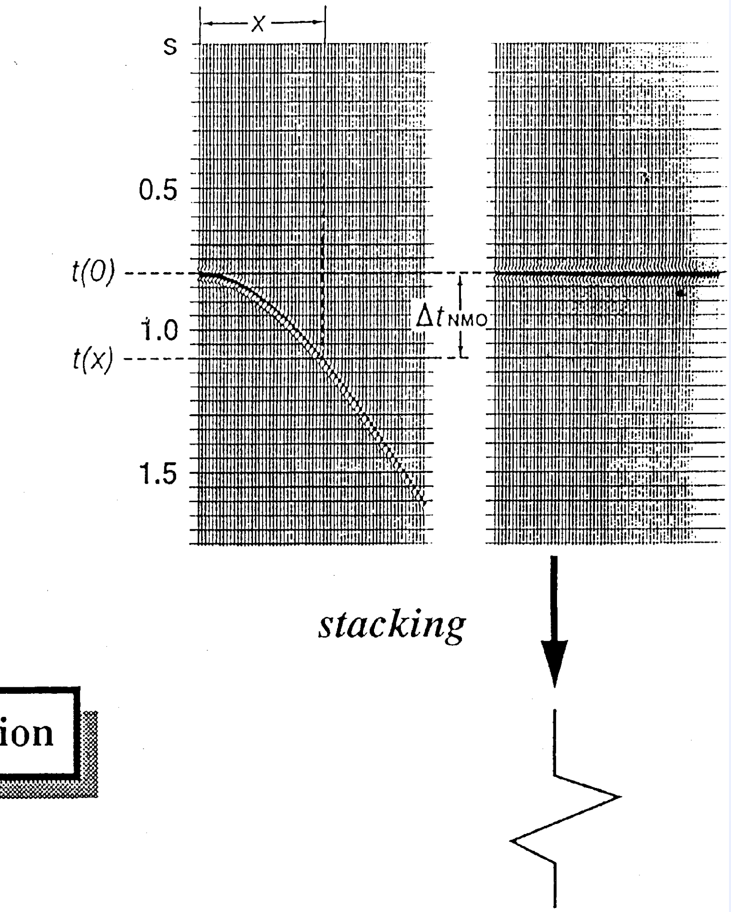


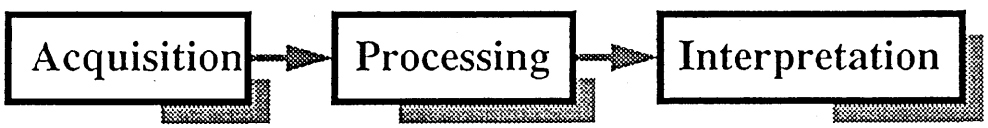
- Oil tends to collect in sandstone (lighter than water)
- It is difficult to estimate velocity models near a salt dome

The Objective of Seismic Surveying is to Supply Images of Subsurface Structures

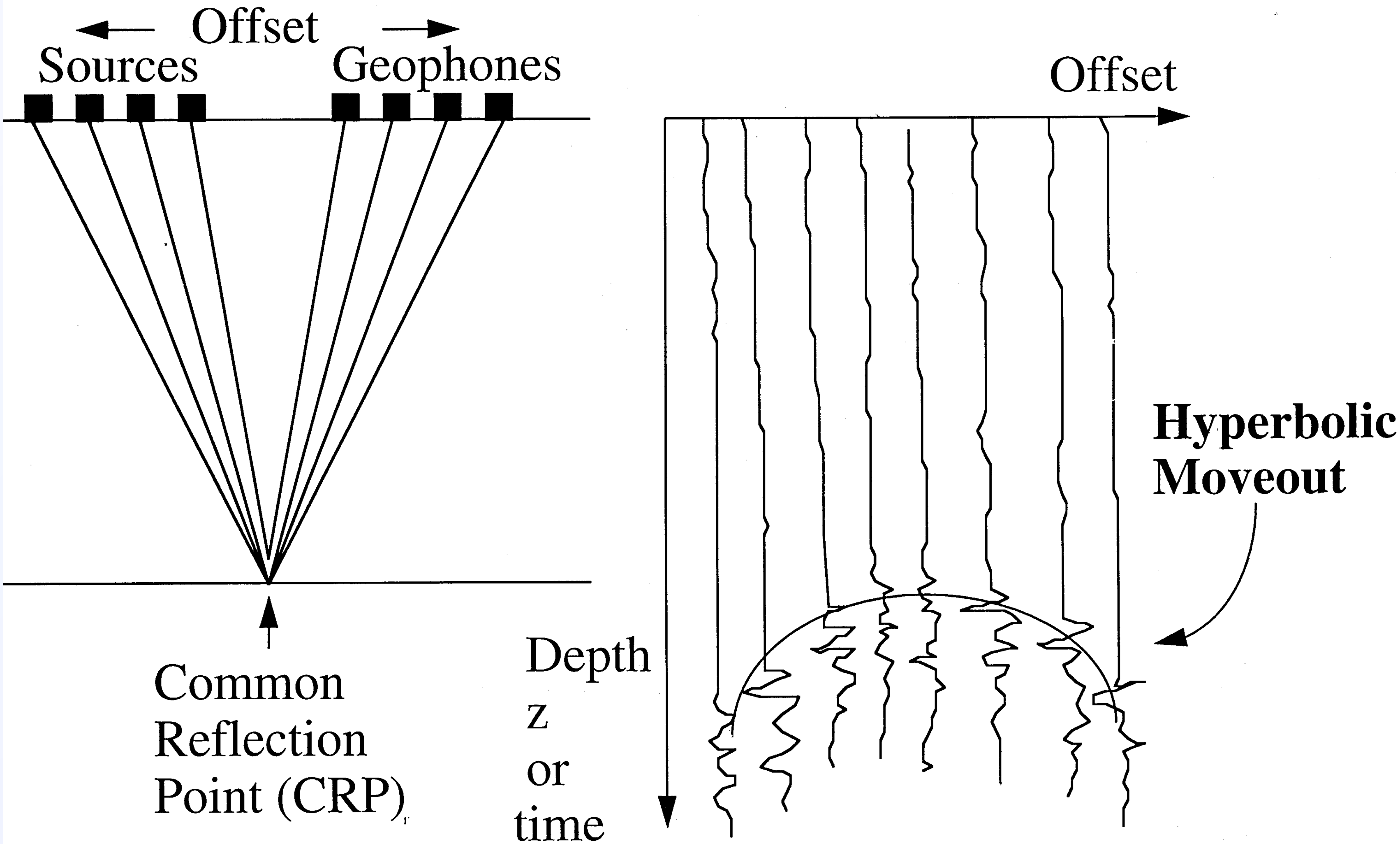


Common Reflection Point (CRP)



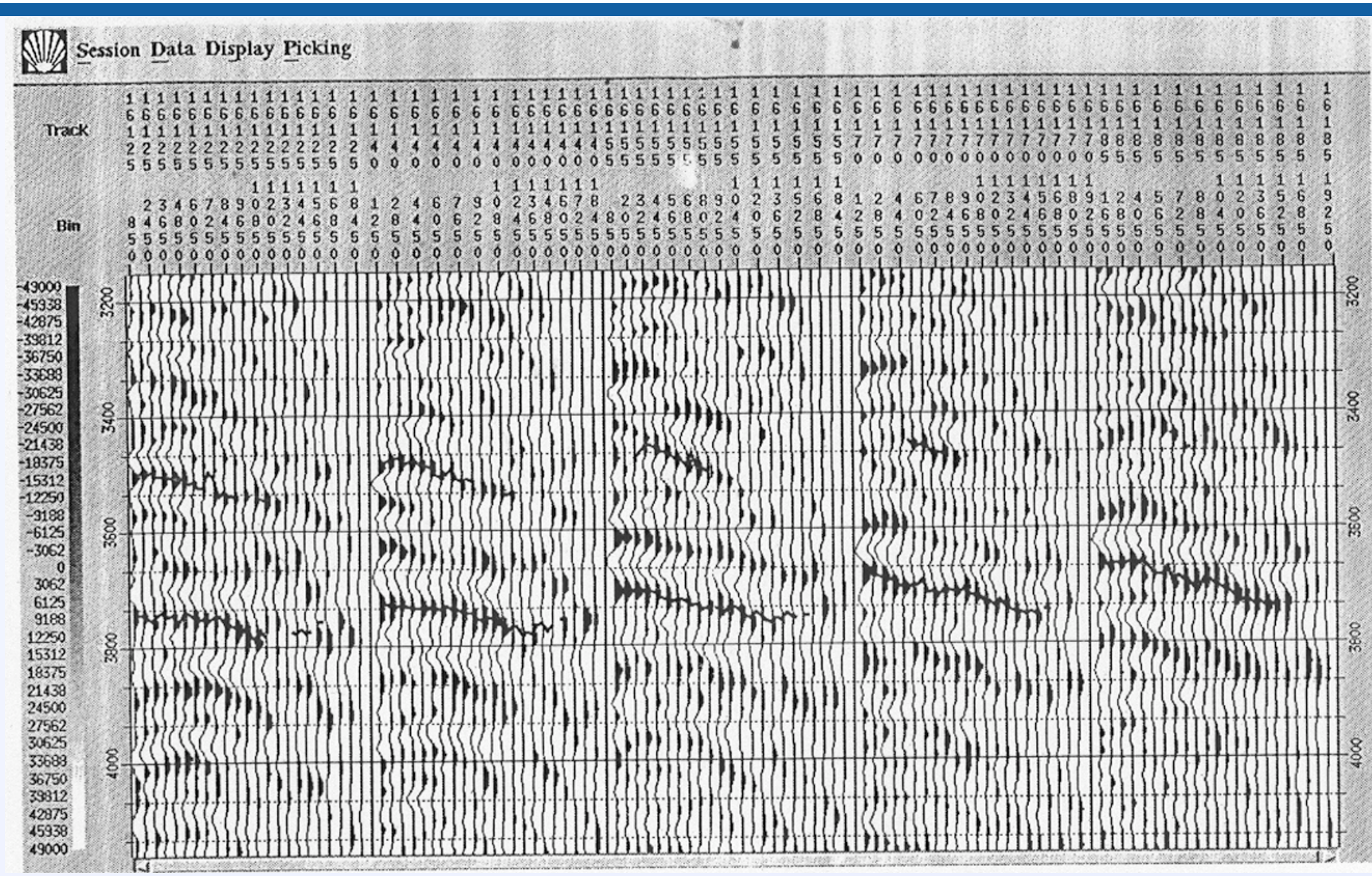


A Common Reflection Point (CRP) Panel is Generated Using Multiple Offsets



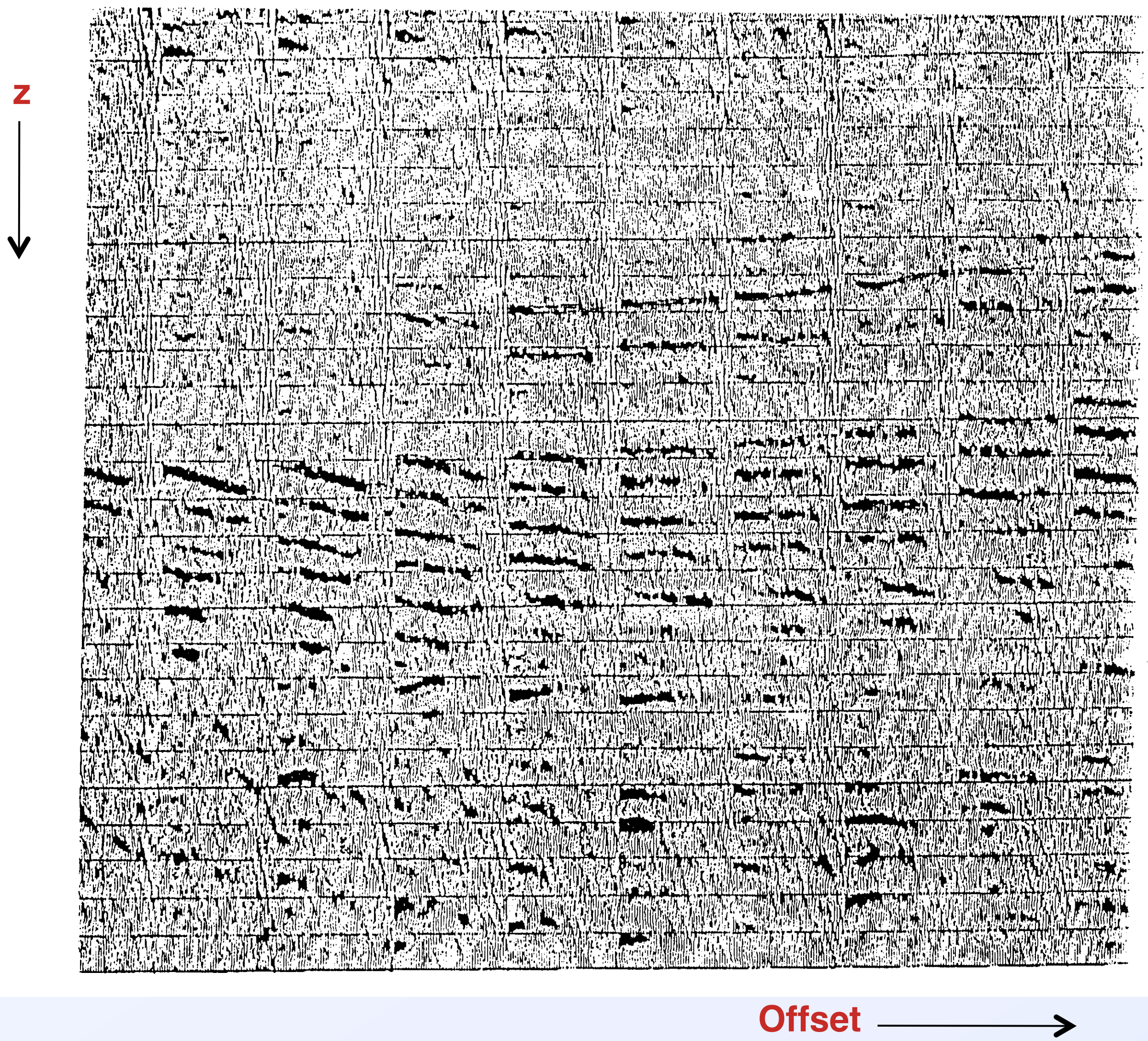
We Plot Common Reflection Point (CRP) Panels in Mosaic Form for Analysis

z

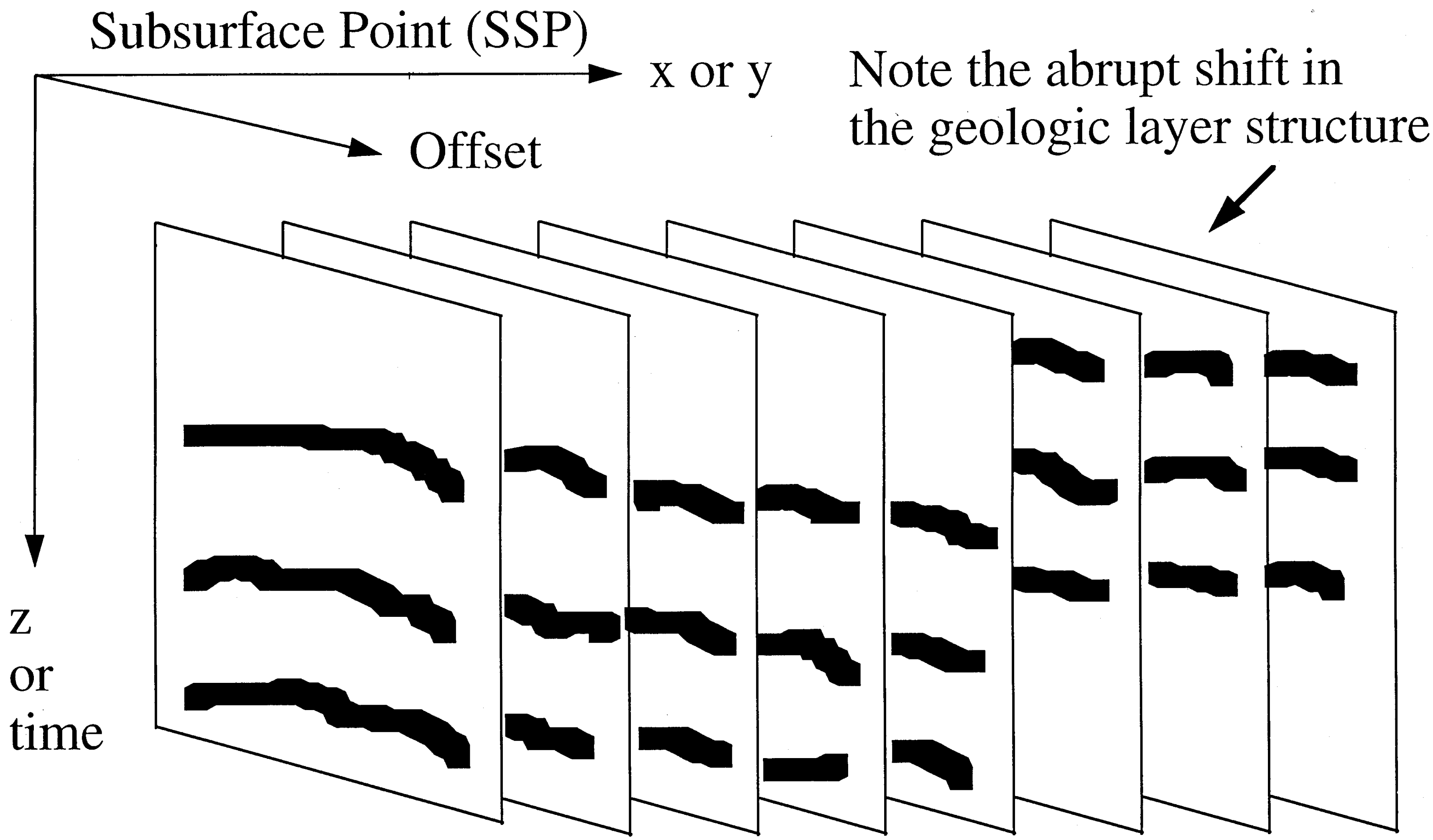


Offset

Real CRP panels are plotted side-by-side in "mosaic" fashion

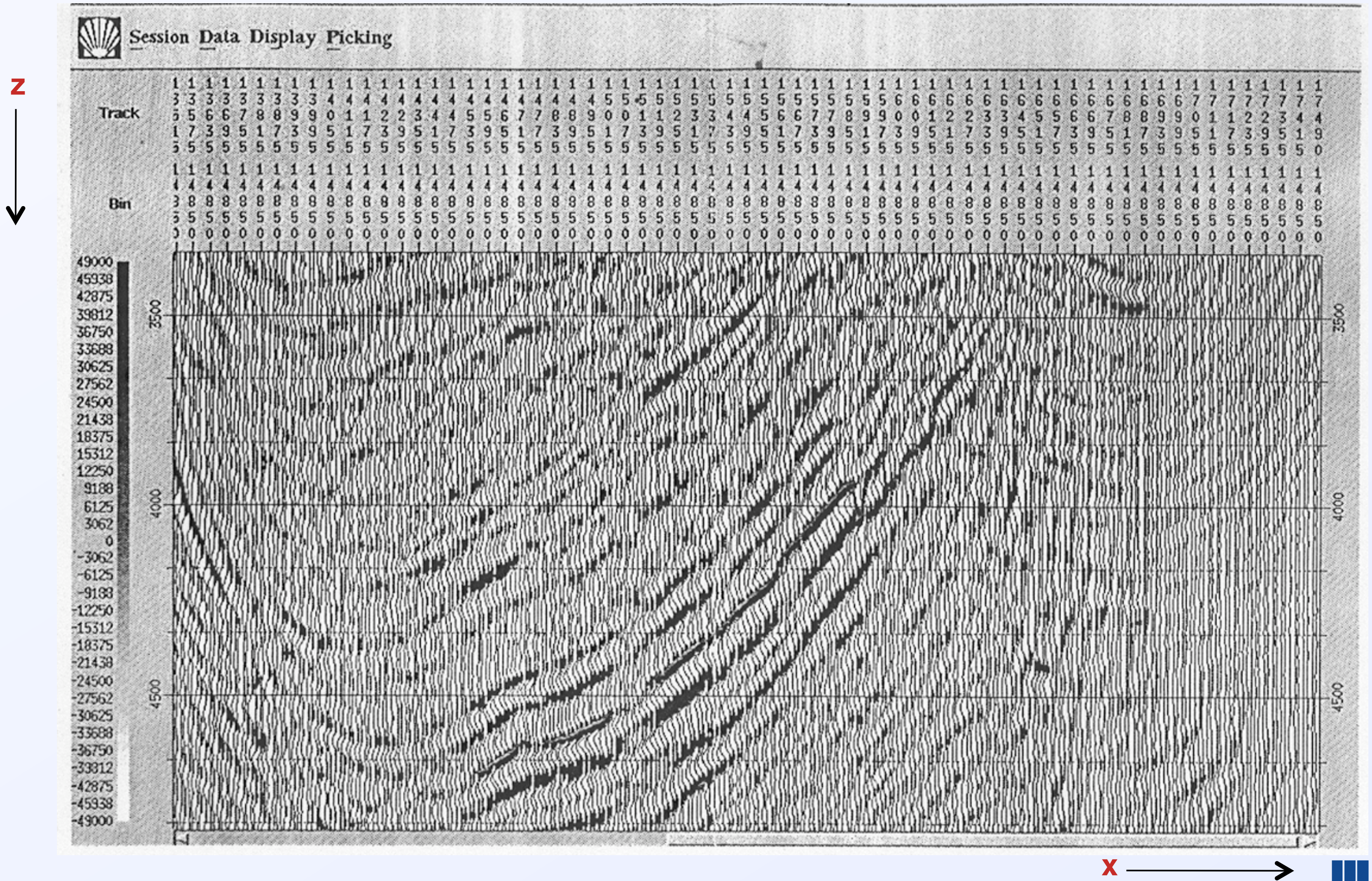


Multiple CRP Panels Create a 3D Data Set for the Subsurface



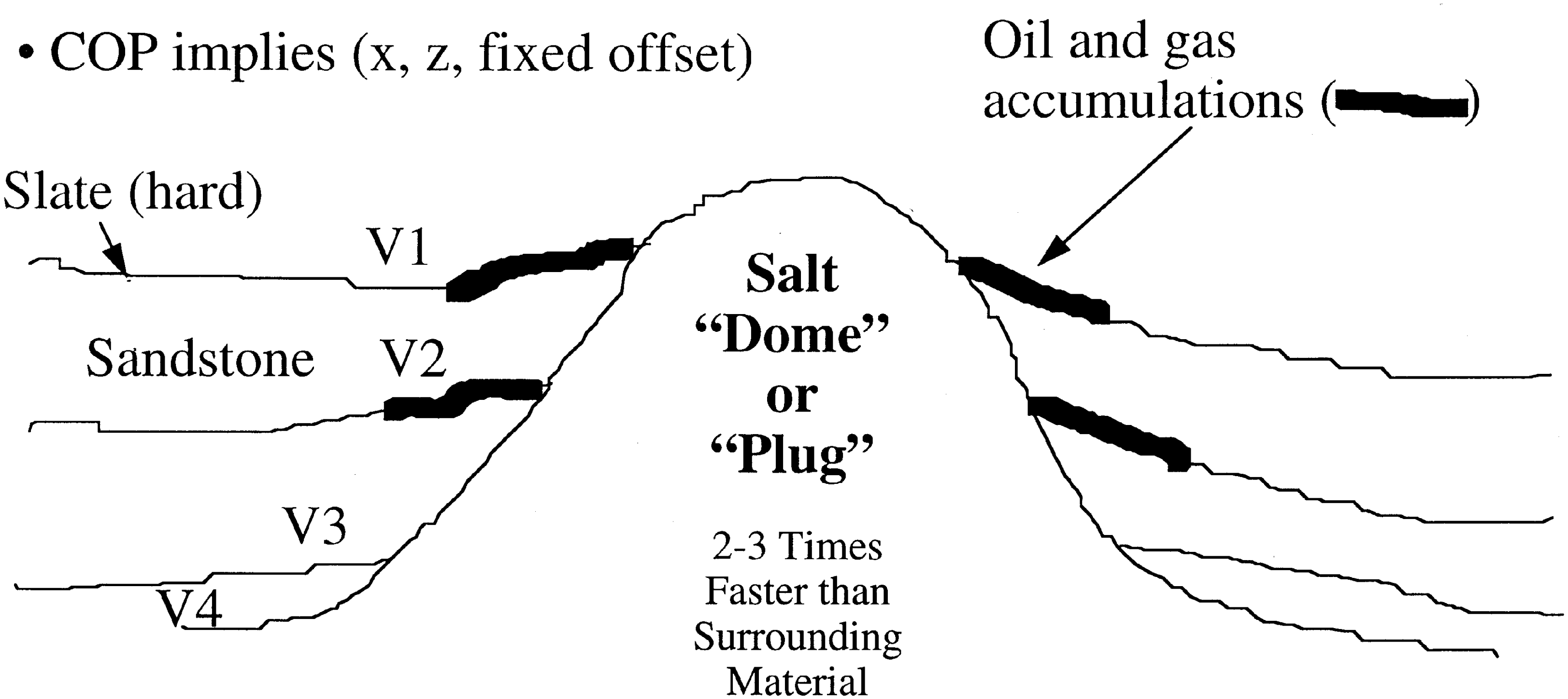
A Common *Offset* Panel (COP)

is a Slice Through 3D Space Along the x and z Directions



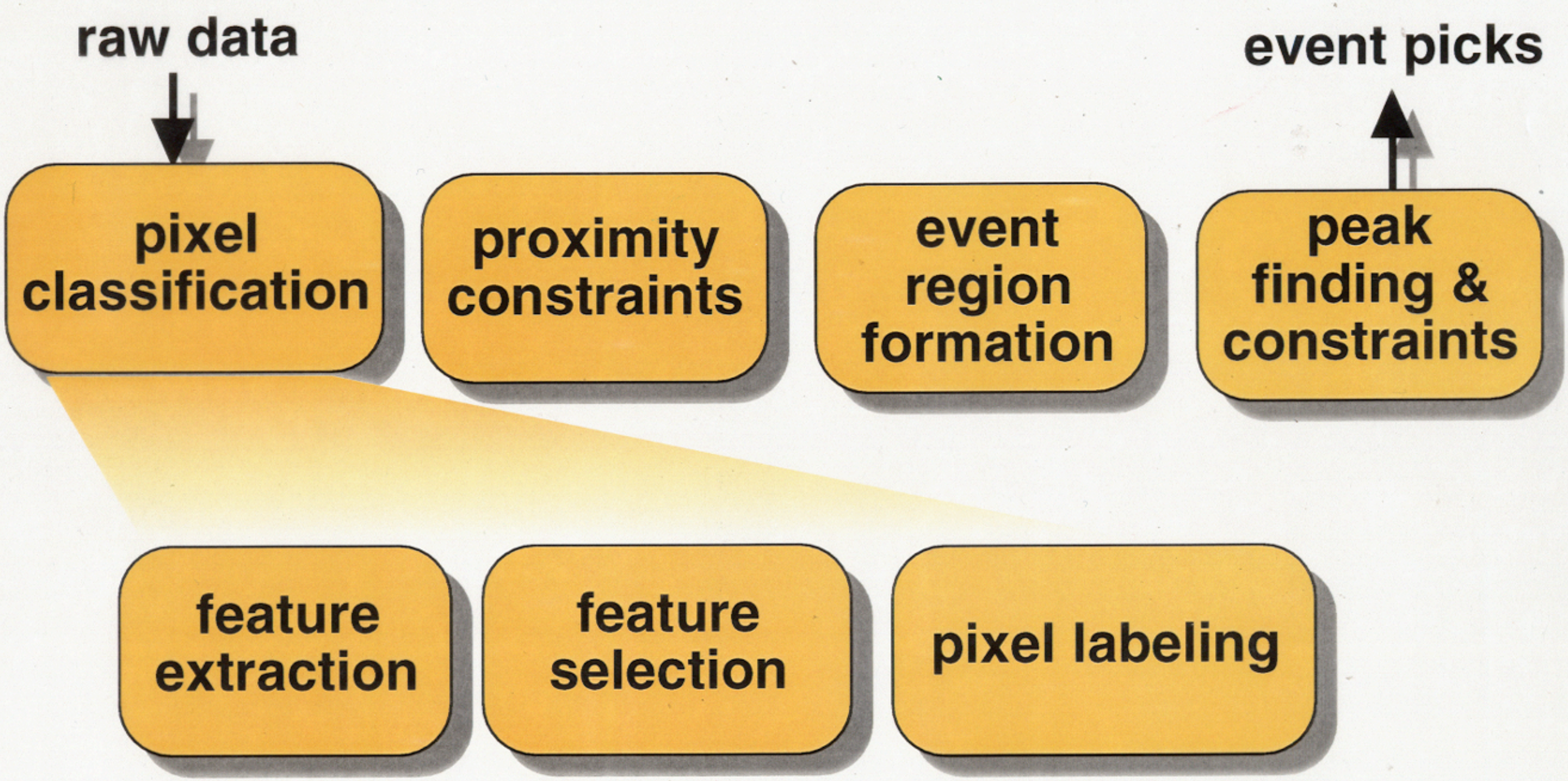
Common offset panels are analyzed to find geologic structures

- COP implies (x, z, fixed offset)



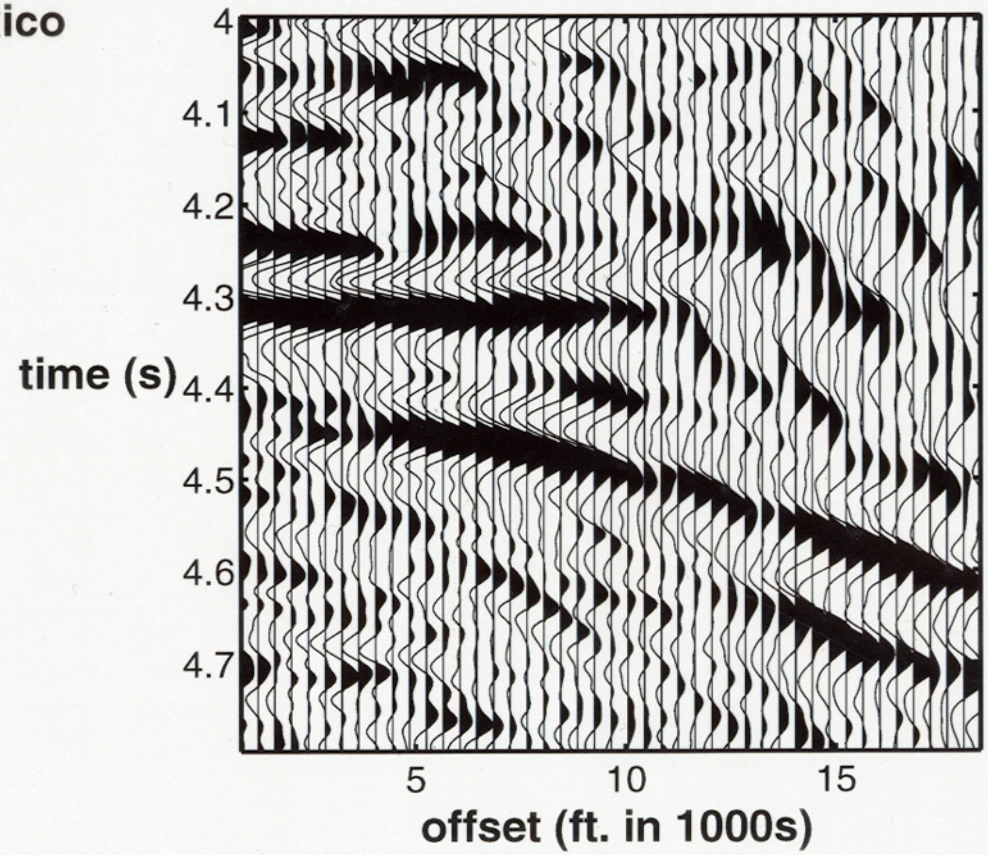
- Oil tends to collect in sandstone (lighter than water)
- It is difficult to estimate velocity models near a salt dome

Processing flow

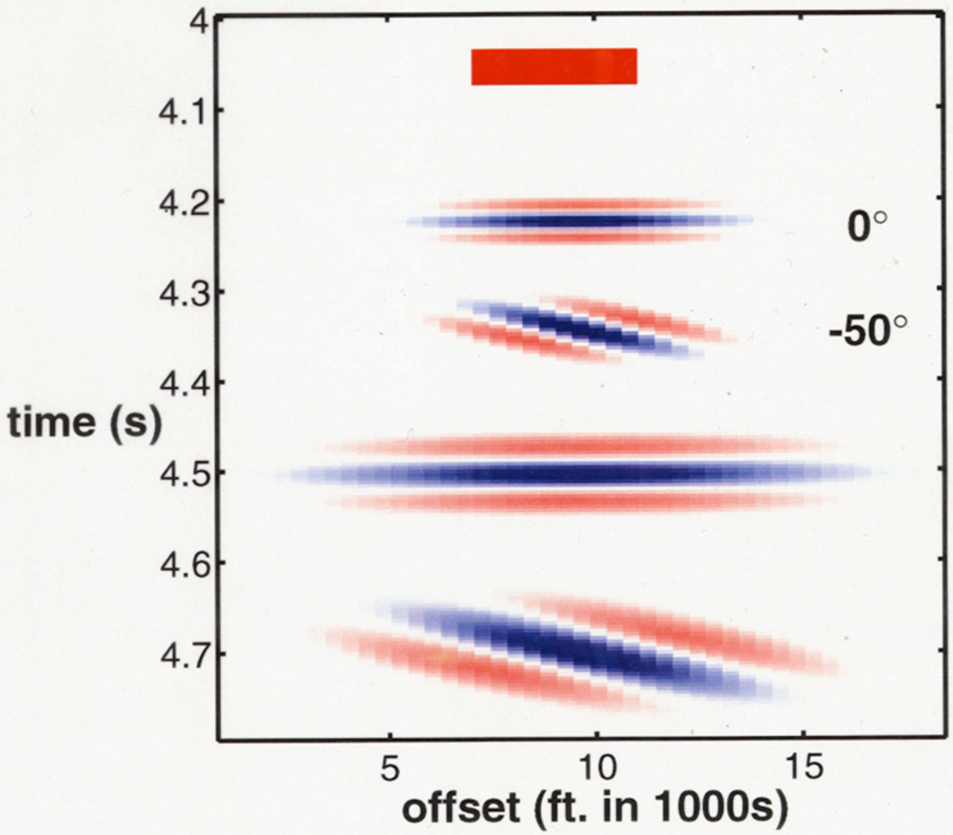


Pre-stack migrated data (raw data)

- Gulf of Mexico
- 2D dataset

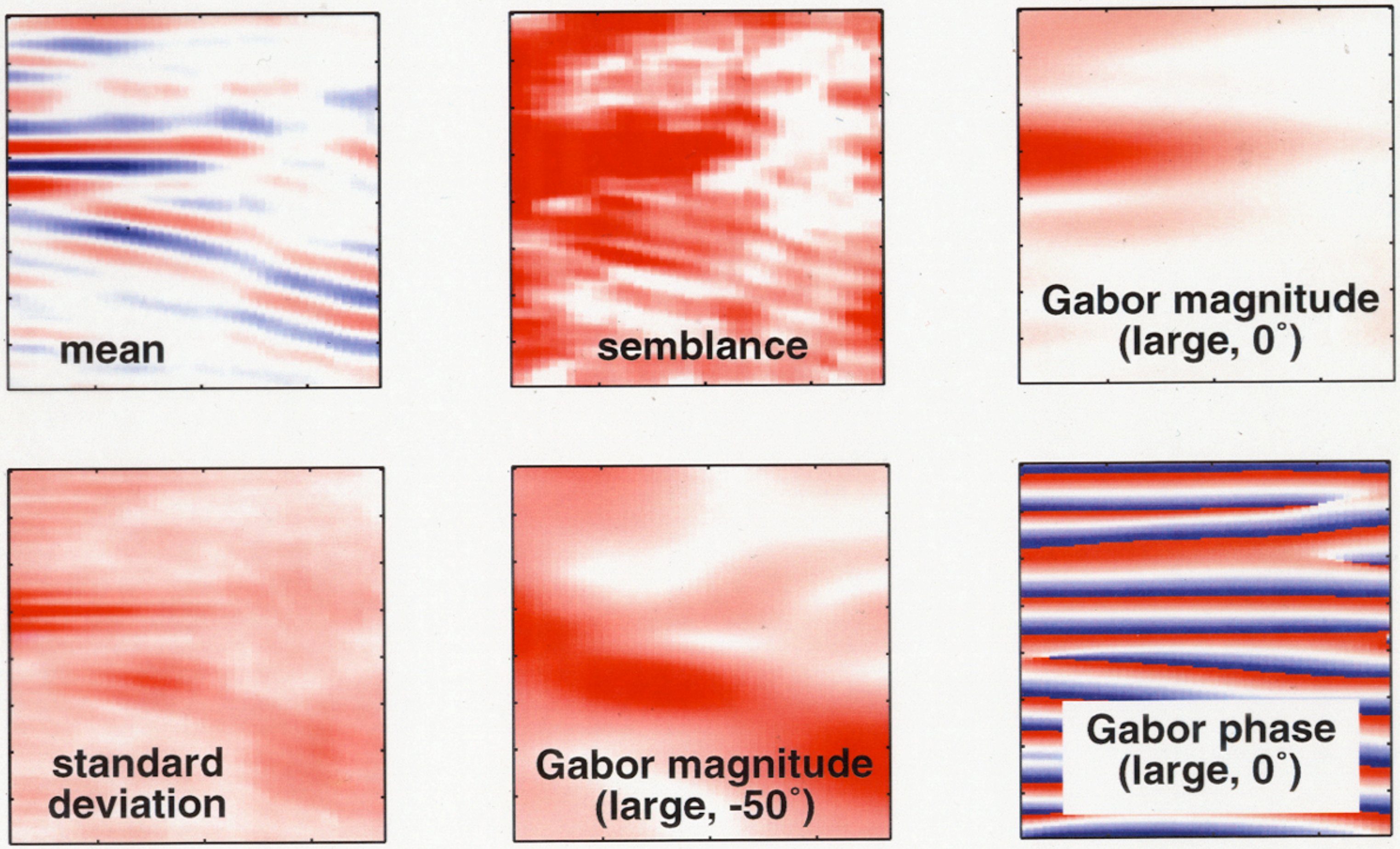


Useful features of the raw data

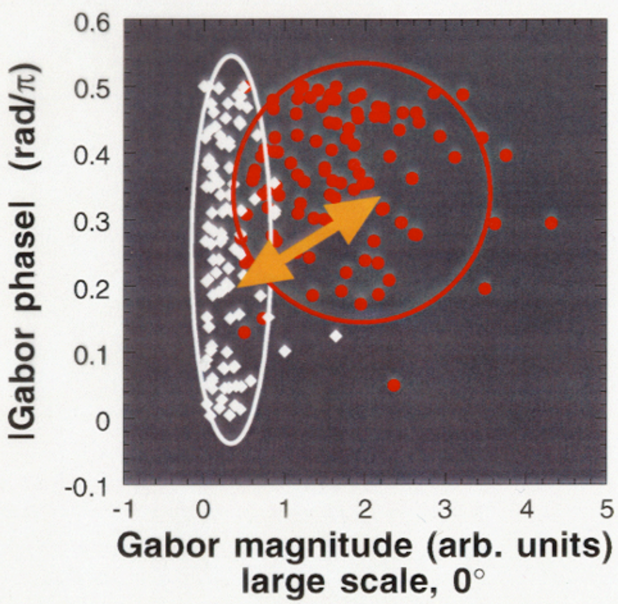


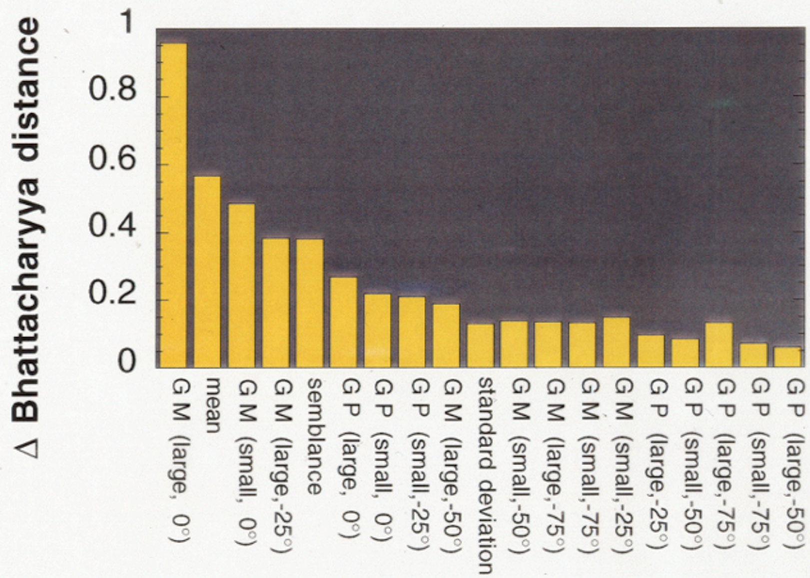
- statistical moments
  - mean
  - standard deviation
  - moment over red box
- semblance
- Gabor transforms
  - magnitude & phase
  - 2 scales
  - 4 angles
    - 0°,-25°,-50°,-75°

Event feature images are formed



Features are ranked via Sequential Forward Selection algorithm



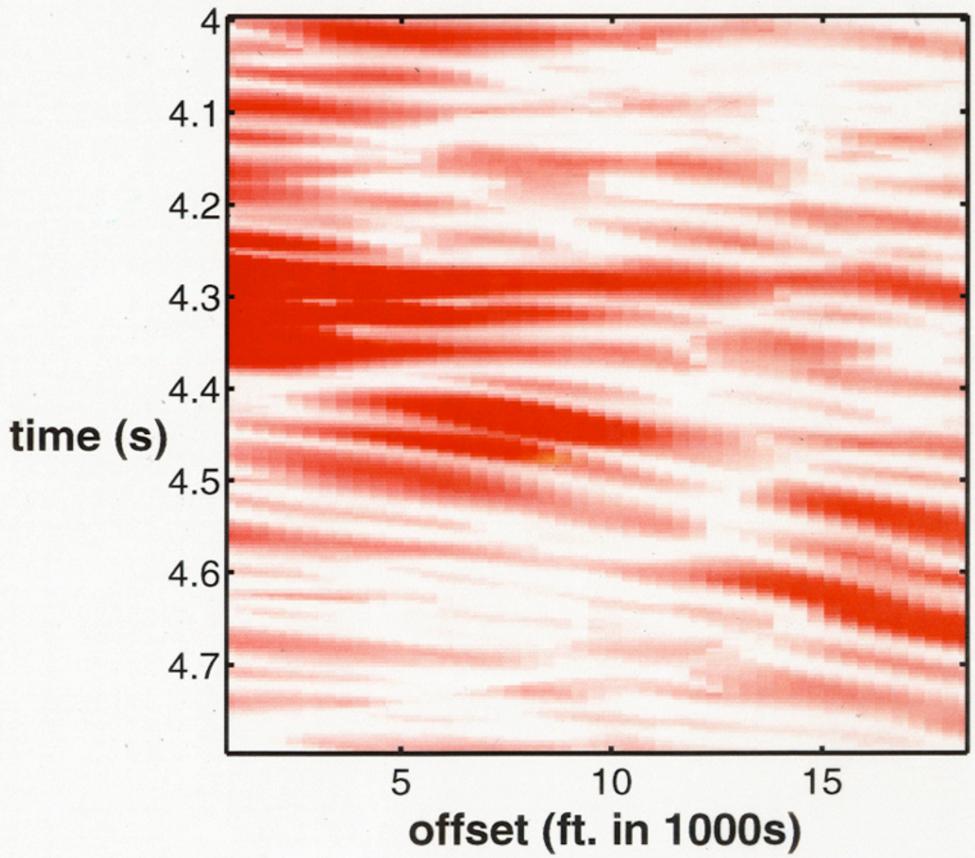


distance between event and background cluster used

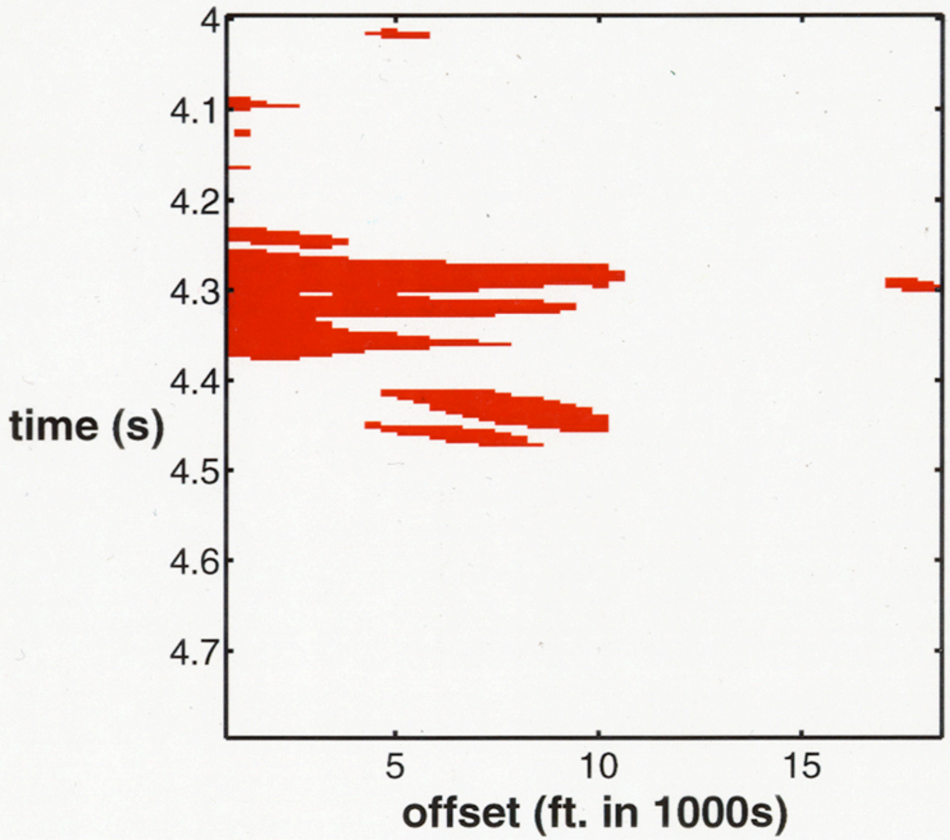
GM = magnitude of Gabor transform
GP = phase of Gabor transform

Posterior probability image using event features as input

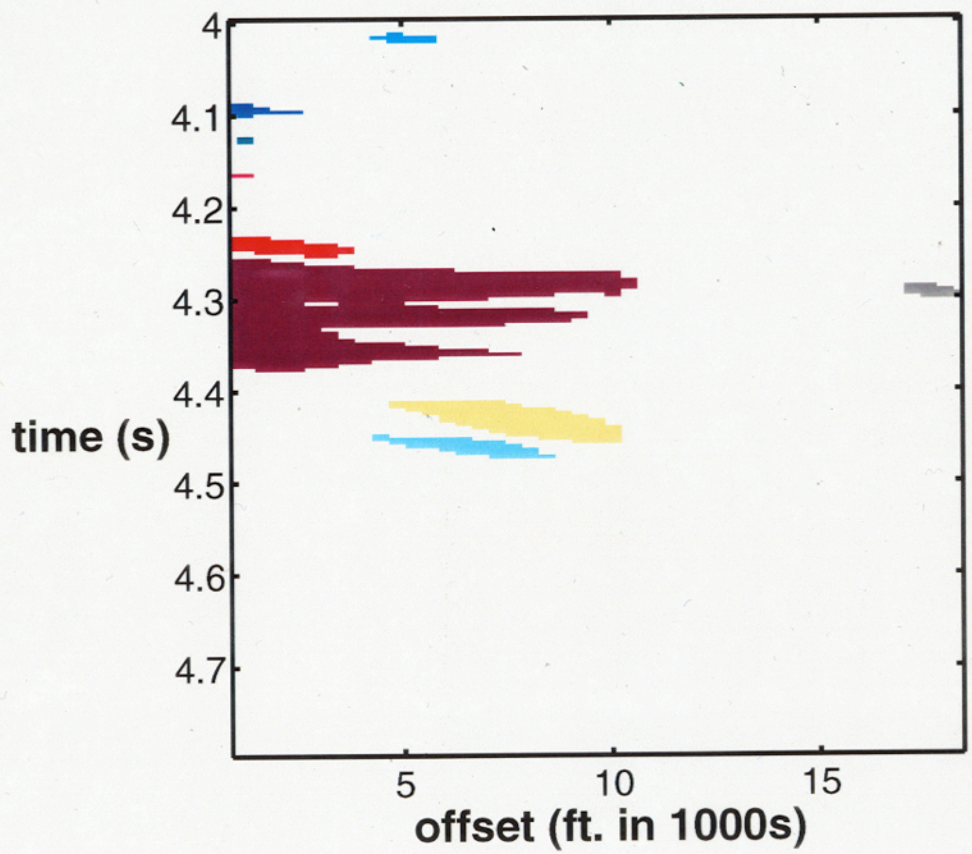
- training set (hand picked)
  - 107 events
  - 100 background
  - 20 out of 468 CRPs
  - 0.5% of picks
- probability of correct classification
  - 95% ± 4%
- key:
  - red = event
  - white = background



Binary labeled image

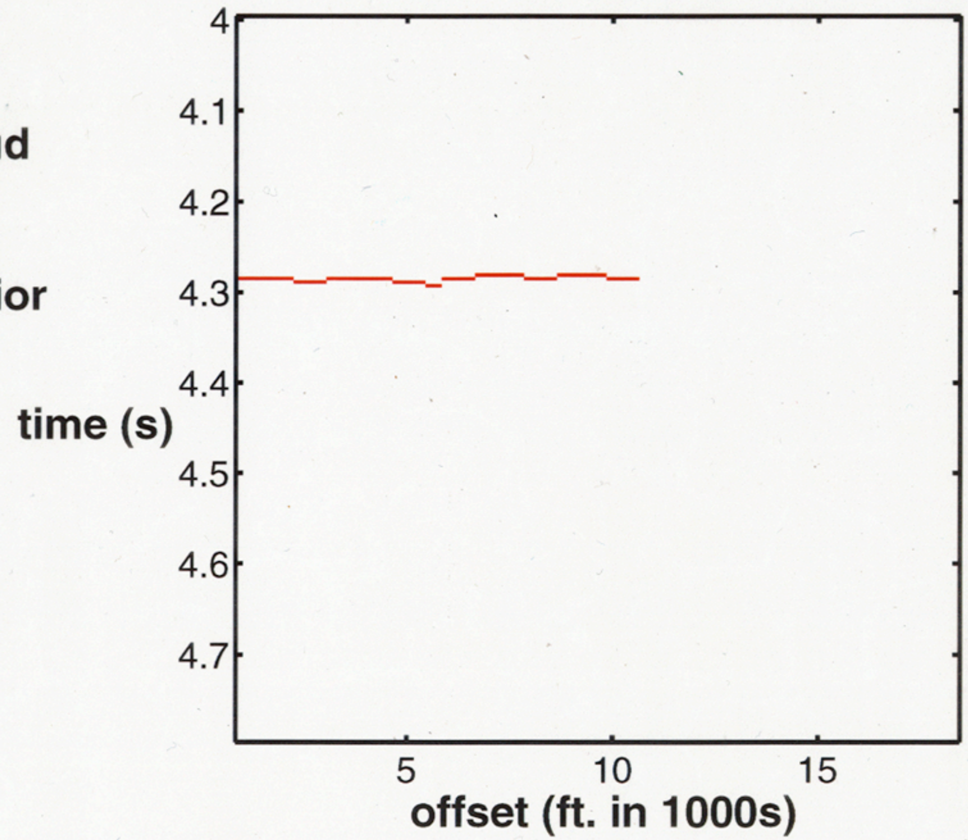


Connected components labeled image

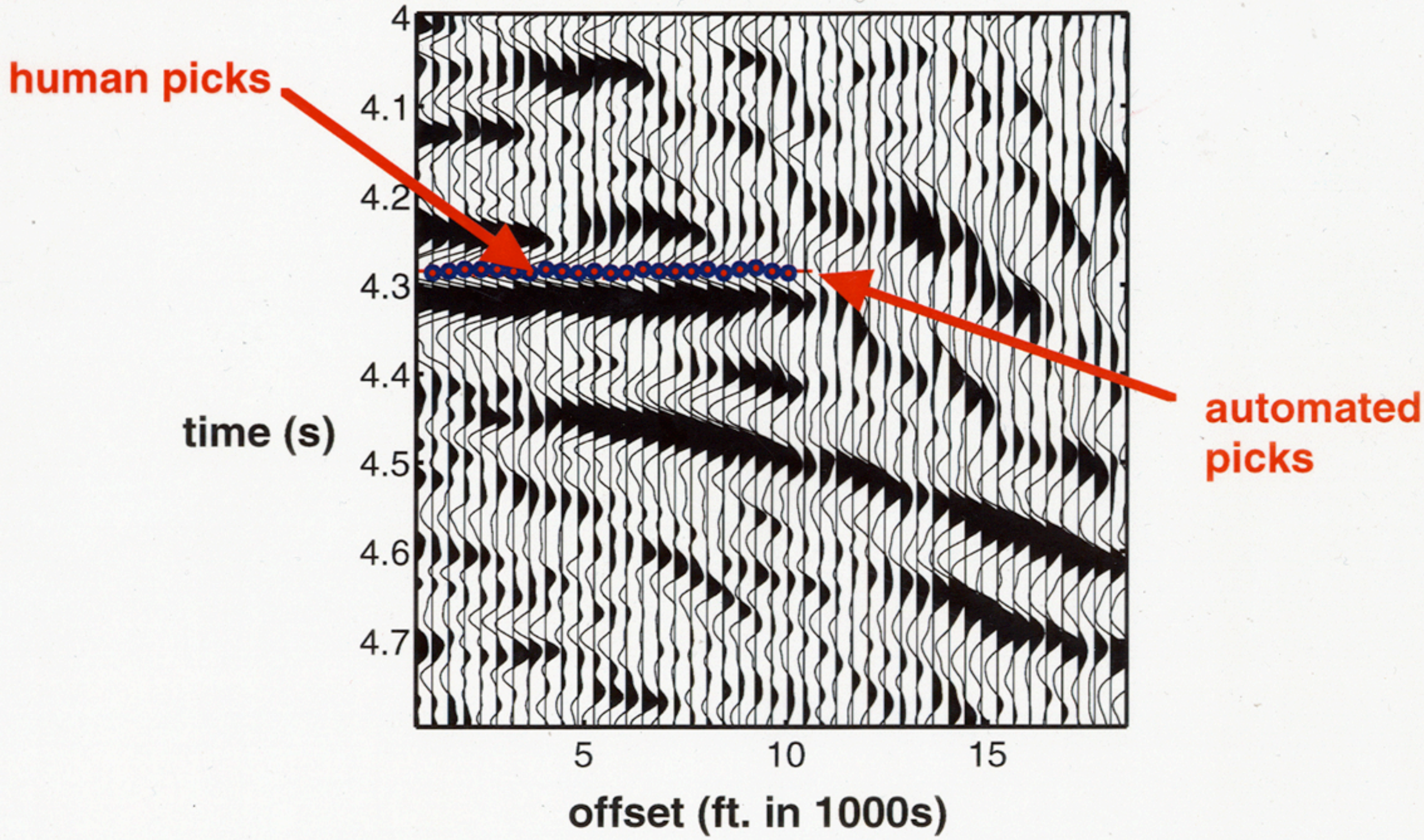


Event image

- size
- one time / offset / cloud
- continuous
- max posterior probability

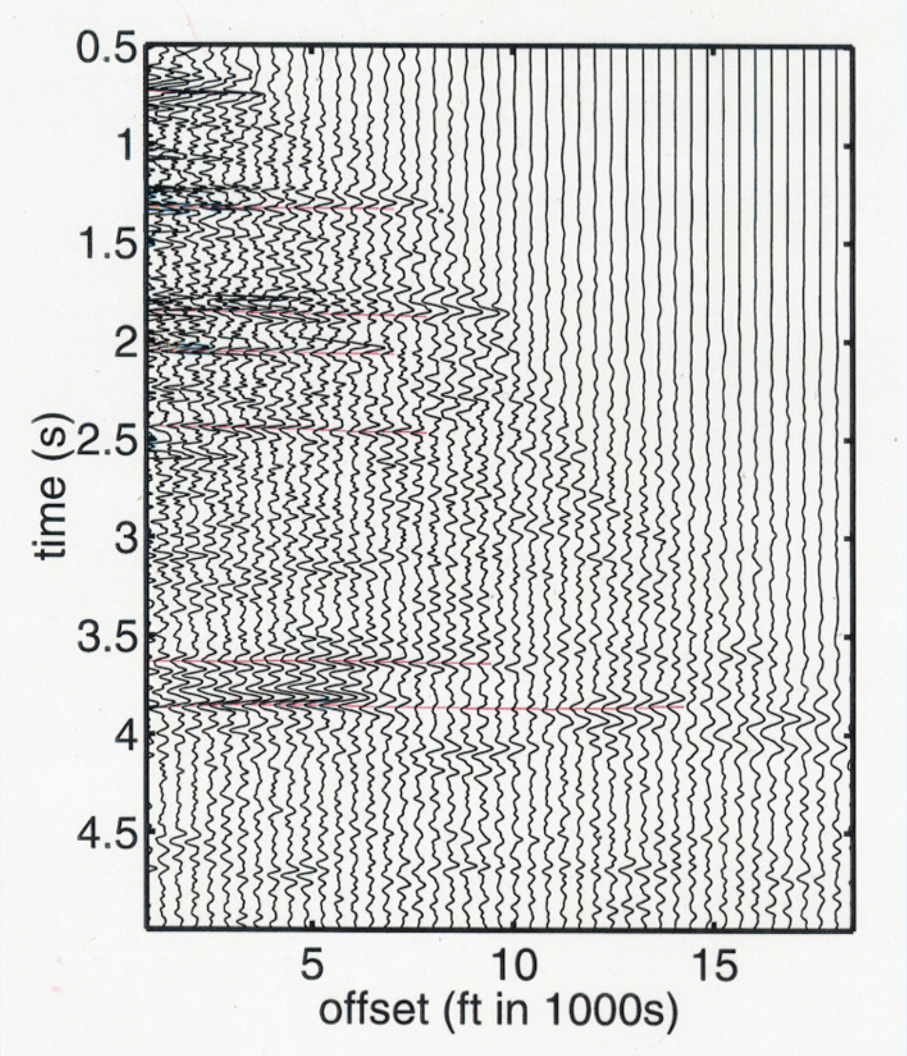


Automated picks compared to human picks



A Full “Picked” CRP Panel:

The Automated Picks Are Displayed as Red Lines



The Automated Picks Match the “Human Picks”

Discussion and Summary

- Similar problems in other disciplines have been worked using statistical signal and image processing algorithms along with the physics

- Please see the references

- I hope this presentation has stimulated ideas for interdisciplinary research

References

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Lawrence Livermore National Laboratory

Extra VG's

Grace A. Clark

There is a velocity analysis bottleneck in pre-stack migration